Closed / access?

[illegible]

Performance assessment of systems

0117 9102 2660

ABSTRACT

Water distribution systems are often susceptible to failure events, mainly due to component malfunctions, increase in demand and pollution events. However, levels of service to the consumers cannot be compromised. Therefore, to understand the behaviour of distribution systems, performance assessment is important.

In this thesis, problem of failure events in water distributions system is discussed and the causes of failure are described. Component failures are selected to simulate the extreme situations in the distribution systems. Random nature of the component failures are simulated by way of employing a Monte Carlo technique based on the failure probabilities of the components. The methodology was illustrated with an example application.

Appropriateness of existing network analysis methods to simulate failure events is analysed and their shortcomings identified. To demonstrate the impact of component failures, they are simulated with the hydraulic network analysis model. The traditional demand driven network analysis approach is not sensitive to pressure variations in the system. Therefore, simulating failures with demand driven analysis methods produces inaccurate flows at the nodes.

The pressure dependent demand analysis on the other hand, is capable of accommodating the flow redistributions in the water distribution network, caused by failure events. The pressure dependent functions used in the analysis are meant to predict the flows that are consumed by the secondary networks (tree network supplied from primary node). However, representing the secondary network behaviour by using only a few coefficients (as in the PDD functions) do not always results in correct predictions.

An alternative method that is based on micro level models (secondary networks) is proposed. Micro level models try to simulate the exact network conditions, taking into account of the consumers piping arrangements. Applying micro level models to a large real network will be a tedious process, as the size of the network will increase by many folds.

To avoid the difficulties in the micro level modeling, a method based on artificial neural networks (ANN) is introduced. The ANNs mimic the behaviour of secondary networks in the micro level model. Therefore, instead of physically attaching the secondary networks, ANNs are incorporated with the analysis. The ANN based network analysis model predicts the pressure dependent demand outflows at the nodes.

The behaviour of water distribution system is evaluated using performance measures. Existing performance indicators are reviewed and their shortcomings identified. New measures are proposed that give better insights into the behaviour of the system and also the failure experience of the consumers.

The improved performance assessment method is applied to a case study network and results were explained.

PERFORMANCE ASSESSMENT OF WATER DISTRIBUTION SYSTEMS

BY

M.A. Mohamed Mansoor, BSc (Hons), MSc

A report submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the University of Loughborough.

Loughborough University
Loughborough, Leicestershire, UK

July 2007

ABSTRACT

Water distribution systems are often susceptible to failure events, mainly due to component malfunctions, increase in demand and pollution events. However, levels of service to the consumers cannot be compromised. Therefore, to understand the behaviour of distribution systems, performance assessment is important.

In this thesis, problem of failure events in water distributions system is discussed and the causes of failure are described. Component failures are selected to simulate the extreme situations in the distribution systems. Random nature of the component failures are simulated by way of employing a Monte Carlo technique based on the failure probabilities of the components. The methodology was illustrated with an example application.

Appropriateness of existing network analysis methods to simulate failure events is analysed and their shortcomings identified. To demonstrate the impact of component failures, they are simulated with the hydraulic network analysis model. The traditional demand driven network analysis approach is not sensitive to pressure variations in the system. Therefore, simulating failures with demand driven analysis methods produces inaccurate flows at the nodes.

The pressure dependent demand analysis on the other hand, is capable of accommodating the flow redistributions in the water distribution network, caused by failure events. The pressure dependent functions used in the analysis are meant to predict the flows that are consumed by the secondary networks (tree network supplied from primary node). However, representing the secondary network behaviour by using only a few coefficients (as in the PDD functions) do not always results in correct predictions.

An alternative method that is based on micro level models (secondary networks) is proposed. Micro level models try to simulate the exact network conditions, taking into account of the consumers piping arrangements. Applying micro level models to a large real network will be a tedious process, as the size of the network will increase by many folds.

To avoid the difficulties in the micro level modeling, a method based on artificial neural networks (ANN) is introduced. The ANNs mimic the behaviour of secondary networks in the micro level model. Therefore, instead of physically attaching the secondary networks, ANNs are incorporated with the analysis. The ANN based network analysis model predicts the pressure dependent demand outflows at the nodes.

The behaviour of water distribution system is evaluated using performance measures. Existing performance indicators are reviewed and their shortcomings identified. New measures are proposed that give better insights into the behaviour of the system and also the failure experience of the consumers.

The improved performance assessment method is applied to a case study network and results were explained.

ACKNOWLEDGEMENTS

I am deeply indebted to my supervisor Dr. Kala Vairavamoorthy, currently Professor of Sustainable Urban Infrastructure Systems at UNESCO- IHE Institute for Water Education, Delft, The Netherlands for encouraging me to pursue the doctoral researches studies in the UK. His guidance, encouragement, constructive criticism and the support for this research has been invaluable to me. On personal front, I could never forget the support and assistance Dr. Kala Vairavamoorthy has provided me during my PhD studies and throughout my stay in UK.

I would also like to give my special thanks to Dr. Sunil.D. Gorantiwar for his support and encouragement during the last year of my research.

I would also like to mention my sincere gratitude to Mr. Ian Smout for his valuable advice and the support in submitting the thesis.

The following are thanked for providing data for analysis and for their co-operation and help during field visits:

- National Water Supply and Drainage Board, Sri Lanka
  Mr. Santha Fernando, Deputy General Manager-Training
  Dr. Lalith Kaluperuma (Senior research engineer)
- Water Board, Kalutara Sri Lanka
  Mr. Dhammika Perera (Chief engineer)
- MWH High Wycombe,UK
  Mr. Jivir Viyakesparan (Principal engineer)

I am thankful to Dr.Harsha Ratnesooriya, and Dr.M.Z.M Malhardeen, University of Moratuwa, Sri Lanka, for their constructive comments during my field visits.

I would like to thank my friends and colleges at Loughborough University. In particular thanks are due to the following for their valuable contribution in the form of academic help and moral support: Mr. Harshal Galgale, Dr.Sachin Shende, Dr.Jimin Yan, Mr. Huipeng Li and Mr. Yibo Shen.

Heartfelt thanks are expressed to my wife Ilmah, for her patience, understanding and forbearance.

Finally, to my parents for their encouragement and support always.

TABLE OF CONTENTS

CONTENTS *PAGE*

CHAPTER 4

PRESSURE DEPENDENT DEMAND IN WATER DISTRIBUTION SYSTEMS

CHAPTER 6

SIMULATION AND APPLICATION

LIST OF TABLES

TABLES **PAGE**

LIST OF FIGURES

NOTATIONS

NOTATIONS	*DEFINITIONS*
$A(i)$	Nodal availability at node i
AD_i	Adequacy at node i
AE_{il}	Expected value of nodal availability considering link l
$A(i)_l$	Nodal availability with link l operational
$A(i)_{ll}$	Nodal availability with link l non operational
ANN	Artificial Neural Network
AR_i	Allocation ratio for the i th node
$\overline{AR}$	Average of the allocation ratios
a_f	Ageing factor (1/year)
ad_i	Actual inflows to the i th node in the system
$a_{i,s}$	Performance rating of node i during the time period s
av_i	Availability during time period i
a_l	Probability that link l is available
B	Coefficient of breakage rate growth
b_f	Failure factor (1/year)
C	Capacity rate in units of discharge lost
CT	Total capacity required
C_j	Numerical equivalent for the consequences for j th group of consumers at a node
C_1	Correction factor for pipe break frequency

C_2	Correction factor for pipe size
C_i	Consumption at node i
cr	Resistance time
c	Period of time between failure occurrence and beginning of repair
D	Diameter of pipe
DD	Demand driven analysis
DSR_{xi}	Demand satisfaction ratio for $x\%$ of demand to be satisfied for i th node
DEV	Percentage of pipe length in low and moderately corrosive soil
d	Total demand of the system
d_{xj}	Number of nodes where $x\%$ of the demand is not satisfied for j th failure event
d_i	Desired inflows to the i th node in the system
E	Equity of the WDS
EPS	Extended Period Analysis
ε -	Specified tolerance
$\underline{e}_i$ -	Elevation at node i
FDD_i	Fraction of delivered demand at node i
FDV_i	Fraction of delivered volume at node i
F_t	Time factor
F_n	Node factor
F_j^*	Maximum flow during the failure of link j
$F(i,m)$	Nodal unavailability
$F_i(\underline{H}_i - \underline{e}_i)$	Pressure dependent demand function corresponding to node i
f_r	Failure frequency

$f(t)$	Life time probability density functions
$f_s(H_s)$	Probability density function of the supplied pressure head
$f_{dl}(H_d^l)$	Probability density function of the minimum pressure head
g	Base year time
H_s	Head available at source
$H_{s,j}^{\min}$	Head at source below which outflow at node j will be unsatisfactory
$H_{s,j}^{des}$	Head at source above which demand at the node would be fully satisfied
$H_s^{\min}$	Source head above which outflow just begins at any node
H_d^u	Upper bound of the nodal heads
H_d^l	Lower bound of the nodal heads
$H_j^{\min}$	Minimum at node j
H_j^{avl}	Available head at node j
H_j^{des}	Desired head at node j
$h_i^{\min}$	Minimum required pressure at node i
h^*	Desired pressure at node i
$h(t,Z)$	Hazard function
$h_0(t)$	Arbitrary baseline hazard function
h_{it}	Residual pressure at node i during time period t
$h(t)$	Hazard functions
I	Percentage of overlain by industrial development
J_i	Nodes connected to node i

$KLoad(t)$	Demand factor for time t
LH	Length of pipe in highly corrosive soil
M_{max}	Number of pressure violations
m	Index for counting violations of minimum pressure
MF	Mean time between failure events of duration greater than t^*
MLM	Micro level model
MLP	Multi layer perceptron
$MTBF$	Mean time between failures
NS	Number of subsets of components
NC	Number of components in each set
NN	Number of consumer nodes
N	Number of simulation runs
N_r	Numerical equivalent of rank
NF	Number of failure events
NSR_{xj}	Node satisfaction ratio for the demand to be satisfied for the j th failure event
$N(t)$	Number of breaks per unit length (km) per year
$N(t_0)$	Number of breaks at the year of installation of pipe
NY	Number of years from installation to first repair
N_f	Number of failures in a time period
N_r	Number of repairs in a time period
NPN	Number of pressure nodes
nl	Number of links
n_c	Total number of consumer groups

n_r	Total number of ranks
n	Total number of consumer groups
n_{xi}	Number of failure out of total events when $x\%$ of the demand is not satisfied
n	Integer
η_r	Repair rate of pumps
P	Absolute pressure within the pipe
$p(j)$	Probability that only link j fails
P_j	Numerical equivalent for importance for the j th group of consumers at a node
PT	Pipe type
$P_{pipe}(k)$	Probability of pipe k failure
$P(\phi)$	Probability that all the pipes are available
$P(S_j)$	Probability of a subset of link S_j, is unavailable
$P(l)$	Probability that only pipe l is unavailable
$P(l,m)$	Probability that two components simultaneously failing
$\Pr(r,T)$	Probability of r failures in time T
$\Pr(t>t^*,n,T)$	Probability of duration t of n failure event in time T greater than duration
PDD	Pressure dependent demand
PRD	Pressure differential
PR	Required pressure
$PNetwork$	Probability of no pipes being out of action
$PKLoad(t)$	Probability corresponding to the demand factor $KLoad(t)$
Q_l	Probability that link l is non operational
$Q_i(l)$	Flow when pipe l is unavailable

$Q_i(S_j)$	Flow available at node i when S_j is unavailable
$Q_{ext}(i)$	Time-averaged demand at node i
Q_{si}	Mean value of water supply at node i
Q_{ij}	Flow in the network element connecting nodes i and j
$Q_i(l,m)$	Flow at node i when two components are unavailable
q_j^{avl}	Flow available at node j
q_j^{req}	Flow required at node j
q_i	Flow at node i
R_n	Nodal Reliability
R_{sm}	System reliability (the minimum of the nodal reliabilities)
R_{ni}	Nodal reliability at node, i node number
R_{sa}	System reliability (the arithmetic mean of the nodal reliabilities)
R_{sw}	System reliability (the supply weighted mean of the nodal reliabilities)
RBF	Radial basis function
RC	Discharge reliability factor
RV	Volume reliability factor
RF	Overall reliability factor
R_V	Volume reliability factor
R_{nw}	Network reliability factor
R_l	Probability that link l is operational
RES	Percentage of pipe overlain by residential development
REP	Number of repairs

R_l	Probability that link l is operational
$r_i(l,m)$	Reliability at node i when two components are unavailable
$r_i(S_j)$	The reliability when S_j is unavailable
r	Rank number
$S(t)$	Survival functions respectively
SL	Surface area of pipe in low corrosive soils
SH	Surface area of pipe in highly corrosive soils
s	State of the node
T	Total time of simulation
T	Simulation period s.
t_i	Length of time periods
$t_{i,j}$	Total duration at run j at node i
t_o	Total operational time
ts	Number of time periods at which node is available
t_r	Total repair time
tr	Expected duration of repair
ta	Age of pipe from first break
u_i	The unavailability of a component
V	Volume shortfall during a single failure or an entire time period
VT	Total volume required
V^{avl}	Available volume,
V^{req}	Required volume
V_T	Total volume supplied at all runs

$V_{j,i}$	Fraction of volume supplied to node i
W_i	Weight factor for the i th node in the system
WDS	Water distribution system
x_i, y_i	Regression coefficients
Z, b	Vectors of covariates and coefficients
Z	Vector of covariates affecting the pipe deterioration
$\lVert \ \rVert$	Euclidean norm
α	Vector of coefficients estimated using regression
α_i, β_i, h_i^*	Constants for particular node
a_0, a_1, a_2	Regression coefficients
Δh_{ij}	Head loss across the element between nodes i and j
ϕ_{ij}	Head flow relationship for the network element between nodes i and j
μ	Mean
σ	Standard deviation
μ_r	Failure rate of pumps
θ, β	Scale and shape parameters respectively
θ_0	Baseline value
λ	Failure rate
μ	Expected period of time between successive failure occurrences

CHAPTER 1

INTRODUCTION

1.1 Introduction

Water distribution systems (WDS) are one of the most important lifeline infrastructure systems. The Levels of Service (LOS) provided by the WDS are often compromised by failure events (component failures and increases in demand). During failures, WDS experience a reduction in pressure and as a result a shortfall in nodal outflows. Compromising consumers' levels of service is not acceptable. Therefore, it is important to evaluate the performance of WDS during failure events to understand the reductions in LOS.

Traditionally in water industry satisfactory performance of the WDS was ensured by having conservative design criteria and operating policies (Vairavamoorthy, 1990). The detailed component failure analysis was not performed and the consequences of failure events were not predicted and taken into account. The whole design philosophy was underpinned by a conservative approach rather than based on logical methods of failure and consequence analyses. This may be due to the unwillingness to admit that any designed system may fail under certain conditions and as a consequence of certain events. However, improvements in efficient network analysis algorithms and the need for the optimised use of resources have paved the way to develop new methodologies for performance assessment of WDS.

Performance assessment in WDS has been carried out for quite a long time; initially analytical methods such as conditional probability approach and minimum cutest methods were employed (Wagner *et al.,* 1988a, Vairavamoorthy, 1991). A major shortcoming of these methods is their inability to consider the network conditions arising from failure events. Furthermore they assume that the only criterion for satisfying demand is the availability of water, in addition they fail to accommodate partial failure events.

More recently simulation methods have been employed. These methods are capable of simulating the changes in the WDS due to failure events. However, network simulation based on Demand Driven formulations are not capable of predicting the reduced nodal outflows resulting from the drop in system pressure. This limitation was later over come by introducing pressure dependent demand functions (Wagner *et al.*, 1988b, Vairavamoorthy, 1994, Germanopoulus, 1988, Tabesh *et al.*, 2005) relating the pressure changes with nodal outflows during failure events.

The events that create extreme situations in the distribution system may range from shortage of water through to major plant failures (such as water treatment plants). Often component (pipe, pump and valve) failure events are the primary causes for the supply interruptions in WDS. These impending events may result from ageing components, transient events, intentional sabotage and inappropriate design and construction.

Some of the impending events in WDS are called controlled events (Thorley, 1991) in that the operator and the designer of the system have influence over the occurrence of the failure event, as in the case of transient events; start up of the pumps and valve operations. On the other hand, they have much less if any at all influence on events like natural component failures, power failures etc.

Failure events and their consequences in WDS are unpredictable. In order for a water authority or utility, to provide an efficient supply, it is important that they should understand the behaviour of the WDS during extreme situations.

Failure events in WDS directly influence the LOS provided to the consumers. The LOS during failure events is dynamic in nature. Immediately after the component failure, consumers experience a sudden reduction in the LOS - extreme scenario; followed by a moderate LOS, after the failure has been isolated with a reduction in the system capacity; finally the system returns to normal operational mode after the repairing the failed component.

When analysing failures and comparing the WDS performance, it is important that decision makers select the performance measures that can articulate the levels of service to the consumers. There is no single definition for a good performance measure (as good performance is determined by meeting the expectations of the consumer). The levels of service and the performance of WDS are interrelated and therefore the performance measures should indicate different aspects of the LOS in WDS. In addition, understanding the expectations of the consumers is essential to clearly demonstrate how a particular system is performing against a failure event. This is essential considering the importance of different consumers and the consequences of failure. Existing performance measures are not adequate to show whether the consumers' expectations have been met. As a result there is a need to develop performance measures that provide information on the LOS and the failure experiences of the consumers as well as the WDS.

Currently, reliability, availability and risk measures have been used to evaluate the performance of WDS. These are interrelated, as they are functions of nodal flows and pressure in WDS. The amount of information that can be obtained by these measures is limited mainly, to short falls in flows, failure frequency and the time duration of system unavailability. These measures fail to address the issues related to consequences faced by the consumers. Understanding the failure experience of the consumers is important as the failure experiences vary depending on factors such as types of consumers, time of use, internal piping arrangements of consumers etc. Therefore, development of appropriate performance measures that complement the existing ones is needed, to be able to understand the overall effects on the WDS and the consumers as a result of failures.

Performance assessment methods generally consist of three procedures: failure prediction of components, network analysis and performance measures. There are issues that are needed to be addressed with these procedures of the existing performance assessment methods, in particular with the network analysis model and performance measures. These issues are mentioned below.

WDS component failures are random events. Therefore to understand the behaviour of the WDS, random component failure behaviour should be simulated. This is achieved by performing a Monte Carlo process using appropriate statistical distributions of component failure times (Wagner *et al.,* 1988b). The corresponding failure durations are generated by using repair time distributions obtained from the field data. Once the failure events have been randomly generated from the appropriate distribution, they can be simulated using the network analysis model to understand the consequence of the failure event.

During extreme situations WDS experience reduced pressure and as result consumers receive reduced nodal outflows. Therefore the relationship between the pressure in the system and the demand is important. The network analysis model uses pressure dependent demand (PDD) functions to evaluate the nodal outflows in WDS. These functions are supposed to represent the behaviour of secondary networks of corresponding primary nodes, in other words, the PDD functions predict the flow variations in the secondary networks due to reduced pressures. However, there is no indication of any relationship between the secondary networks and the PDD functions. Furthermore extensive field data is necessary to determine the coefficients that dictate the nature of the PDD relationship. In the mean time, it is possible to develop methodologies that reflect the secondary network characteristics, when evaluating nodal outflows. Such methodologies might lead to modifications in the WDS modelling process. Therefore the present research studies were undertaken to investigate in detail different techniques of hydraulic network modelling and existing performance measures and come out with the new sets of performance measures that describe the performance of WDS in the events of failure and the appropriate hydraulic network model for the newly developed performance measures.

1.2 Aims and Objectives of this Research

The aim of this thesis is to develop an improved method for assessing the performance of water distribution system during extreme events. The specific objectives of the study were as follows:

- To review the extent of the problems associated with existing methods of performance assessment of water distribution systems and to investigate the implications of the proposed modifications.
- To review the existing pressure dependent demand analysis methods and their suitability to be applied in performance assessment.
- To identify modifications required to develop pressure dependent demand analysis that simulate secondary network conditions in the network.
- To review and develop artificial neural networks that simulate secondary network conditions to predict pressure dependent nodal outflows and to integrate it with network analysis.
- To review the existing methods of quantifying the performances and identify the shortcomings of the existing measures.
- To develop appropriate performance measures that reflect the failure experience of the stakeholders.
- To develop a simulation method for risk assessment by combining component failures, pressure dependent analysis model and new performance measures.
- To apply the method to a case study and verify its applicability.

1.3 Research Methodology

The research methodology adopted in this thesis comprises of three key components as shown in Figure 1.1. The main contributions to the methodology are the modified network analysis and the development of new consumer based performance indicators to evaluate the WDS performance during failure events. The failure prediction model used in this research is obtained from the literature and appropriate modifications were carried out on it. The combination of all the three models gives the performance assessment method for WDS.

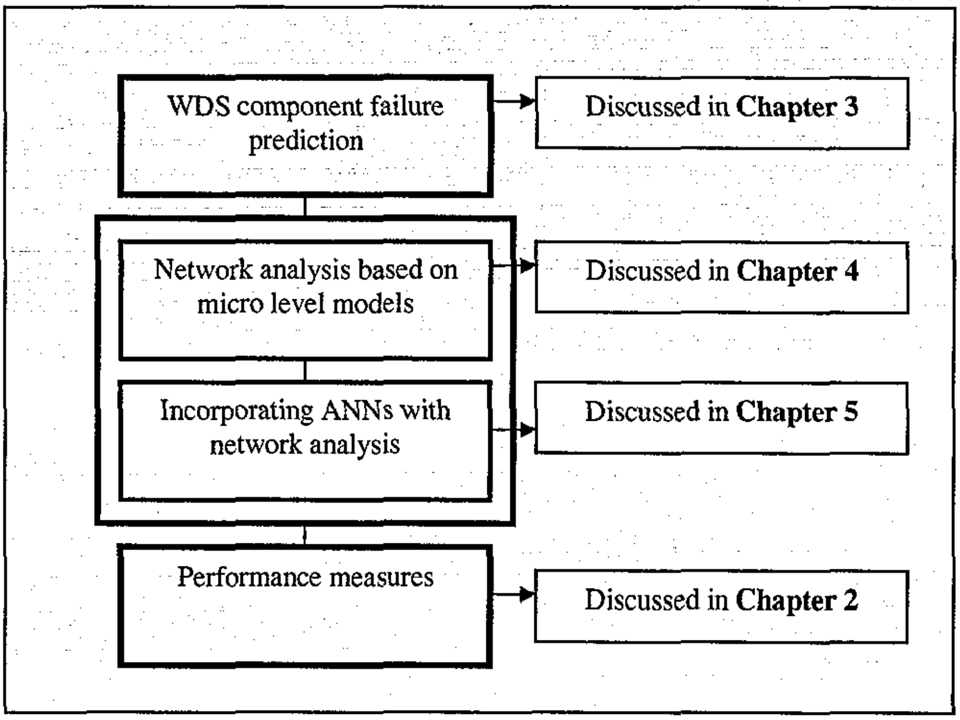


Figure 1.1 Research Components

The main components of the research are the improved hydraulic network analysis method and the introduction of new performance measures. The hydraulic network analysis method is primarily based on the secondary network (tree shaped networks represented by primary nodes) analysis. This is a more satisfactory method as it enables modelling of the actual network conditions, thus reducing the number of assumptions. However the shortcoming in this technique is that number of secondary networks will become exeptionally large for real WDS and also the modelling process will become much more cumbersome. Therefore in order to simplify the secondary network modelling, Artificial Neural Networks (ANNs) are introduced. The ANNs are capable of representing the behaviour of secondary networks or micro level models without physically incorporating the secondary networks into network analysis. The ANNs are trained with the characteristics of the secondary networks. The trained networks will represent the behaviour of secondary networks of corresponding primary nodes.

In this research micro level analysis of WDS is investigated and when applying this method to real networks, application of ANNs along with the network analysis is demonstrated. Therefore hydraulic network analysis proposed in this thesis is the micro level network analysis based on ANNs.

The performance measures developed in this thesis are particularly concerned with the consumers' behaviour. Consequences of failures experienced by the consumers vary depending on the consumer behaviour, times of failure events, internal piping arrangements, and the income levels etc. Therefore when developing performance measures the above factors must be taken into account. The proposed performance measures are developed to complement the existing ones. The new measures indicate the extent of failure consequence in the WDS, especially the supply equity during extreme situations and the failure experience of groups of consumers. These measures express the network behaviour during failures and the extent of impact to consumers.

Component failure prediction model presented in this thesis is based on the model presented by Wagner *et al.,* (1988b). However, slight modifications have been carried out. These are mainly to include: duration at which a component remains in dynamic failed state, and the duration at which the component is isolated for repair. Although there is no significant research contribution to this section, this model is incorporated to complete the performance assessment model. A demonstration of the application of the performance assessment model is given in Chapter 6.

1.4 Thesis Structure

Chapter 2

Performance Measures for Water Distribution Systems

This chapter reviews the existing performance measures used to evaluate the behaviour of WDS including reliability, availability and risk based measures. The applicability of these measures to different situations is investigated and shortcomings identified. Need for consumer based measures is discussed and development and application of new measures explained.

Chapter 3

Component Failure Mechanism

This chapter investigates the factors that influence the component failures in WDS and methods available to predict the failure behaviour of components. In addition different states of the water distribution system during a failure event are explained. The methods of simulating random component failure events are discussed and an appropriate method is selected and applied to an example network.

Chapter 4

Pressure Dependent Demand in Water Distribution Systems

This chapter reviews the existing network analysis techniques; the demand driven and the pressure dependent demand approach. The existing PDD functions are reviewed and their applicability discussed. A comparison of PDD functions and secondary network analysis carried out and the shortcomings of PDD functions identified. The basis that underpins the secondary network or micro level analysis is discussed. Development of micro level models (MLM) and their ability to simulate the PDD behaviour are explained. Application of the micro level model to an example network is presented.

Chapter 5

Artificial Neural Networks in Pressure Dependent Demand Analysis

This chapter describes the development and implementation of ANNs to predict pressure dependent outflow of WDS. The chapter starts with an introduction to different types of ANNs, their corresponding architectures and applications. Particular attention is given to multilayer feed forward neural networks and their applications to water sector. Multilayer perceptron networks are described in detail including data requirements, training, testing and cross validation of the networks. The application of MLP network to represent micro level networks is discussed in detail. Integration of ANN representing the MLM with the network analysis is explained and finally the ANN based network analysis is applied to an example network to demonstrate its capability.

Chapter 6

Simulation and Application

This chapter describes the integration and interaction between the different components of the performance assessment methodology. The methods available to represent component failure events are also described. The developed failure assessment model is applied to a case study network and results discussed.

CHAPTER 2

PERFORMANCE MEASURES FOR WATER DISTRIBUTION SYSTEMS

2.1 Introduction

Performance measures are indicators that describe the behaviour of a system in terms of its tangible operational characteristics. For a water distribution system, performance indicators quantify its behaviour mainly based on the nodal outflows, supply pressure at consumer outlets, supply interruptions, amount of leakage and water quality issues.

The objectives of the water distribution system are the drivers behind the development of performance measures. In this section the water distribution system objectives have been restricted to those of sufficient supply with adequate pressure. Thus only performance measures indicating supply reliabilities such as the reliability, availability and the risk indices are discussed.

The factors that contribute to the frequent interruptions of the water distribution system operation can be mainly categorised into two groups; system demand increase (urbanisation, population increase etc.) and deterioration of assets (component failures, leakage, loss in carrying capacity etc.). Such events cause notable changes in water distribution network conditions and result in reduced flows and residual pressure at consumer outlets. Therefore, it is imperative to understand and quantify such changes in the behaviour of the system that results in unsatisfactory levels of service experienced by the consumers. Hence, the need for appropriate performance measures to articulate the behaviour of WDS.

This chapter discusses the existing performance measures used both in literature as well as in the water industry. Their ability in demonstrating the consequences faced by the consumers during extreme conditions is analysed. Need for the new measures that will assist in predicting WDS performance are outlined and their suitability is demonstrated by comparing them with existing measures.

2.2. Performance Measures in WDS

The main objectives of a WDS are to *"provide an uninterrupted supply of safe water in adequate quantities with sufficient pressure"*. This definition of water supply takes into account the quality, quantity and operational aspect of the WDS such as the interruption to supply and pressure at consumer's outlets (WHO study group, 1987).

The World Health Organisation defines safe water as *"water that does not contain harmful chemicals or micro organisms in concentrations that can cause illness of any form"*. And adequate supply is defined as *"the supply that provides sufficient quantity of water for drinking, culinary and other household purposes to ensure the personal hygiene of individuals. A reliable year round supply should be available near or within the household where the water is being used"* (WHO study group, 1987).

Providing good quality water in sufficient quantities that can be easily accessed are the main criteria to be met by the water utilities. The quality of water to be provided is usually decided based on the water quality guidelines (WHO guidelines, European Union standards, USEPA guidelines etc.). The quantity depends on consumers' needs, income, weather conditions etc. It is important that the quantity supplied is sufficient to meet the hygienic needs of the consumers. Operational aspects of water supply; supply pressure and frequency of interruptions are factors that determine the supply equity, consumer satisfaction and the continuity of the water supply.

Levels of service in a WDS are the conditions that needed to be satisfied in order to meet WDS objectives. Performance measures provide a tangible way to understand the LOS and also the behaviour of the WDS. They translate the levels of service requirements to measurable indicators of the WDS characteristics (such as flow, pressure etc.).

Performance measures are indicators that reflect the ability of the WDS meeting the levels of service. A variety of measures have been defined to monitor various aspects of the performance of WDS. These aspects vary from frequency of interruption of supply through to leakage in the system (OFWAT, 2005). Performance measures employed in the water industry to evaluate the behaviour of water distribution systems can be categorised into different groups depending on the objectives. IWA has grouped the performance indicators of WDS into: water resource indicators, operational indicators, physical indicators, quality of service indicators, financial indicators and personnel indicators (IWA, 1997). Some of the currently used measures have been listed in Table 2.1 below.

Table 2.1: Selected performance indicators for WDS (IWA)

Performance Indicator	Unit
Mains	
Renovation Replacement Valve replacement	% per year % per year % per year
Pump	
Refurbishment Replacement	% per year % per year
Water Loss	
Loss per connection Loss per main	m^3/connection/year m^3/km/day
Service	
Population coverage with service connection Pressure of supply adequacy Bulk supply adequacy Continuity of supply Water interruptions Interruptions per connection Bulk supply interruptions	% % % % % No/1000 connection/year No/delivery point/year

Apart from these, other indicators that reflect the behaviour of WDS have been widely discussed in the literature. These indicators, unlike the ones given in IWA and OFWAT, looks into the function of the WDS in terms of performances of nodes and system (Gupta and Bhave, 1996).

This chapter reviews the available performance measures used in WDS and to propose modification where there are shortcomings. This section particularly focuses on the water supply objective relevant to the supply of sufficient quantities, therefore, only indices concerned with supply to consumers are considered. A comprehensive review of existing performance measures relating the supply aspect of water distribution is given below.

2.3. Existing Performance Measures in WDS

The performance measures in this section refer to indices that represent the levels of service related to the amount of water supplied to WDS the nodes or consumers. The aspects of water quality and conservation are not considered as this thesis is only concerned with the framework of performance assessment with respect to water distribution.

Performance measures are generally used as surrogates to assess the levels of service in WDS. They provide useful information as to how the system behaves during the operation, in particular during extreme situations such as failure events or peak demand periods. Various definitions of performance measures based on issues related to reliability, availability and risk, have been proposed in the literature to suit specific situations (Gupta and Bhave, 1996; Germanopoulos, 1988; Tanyimboh *et al.*, 2001; Shinestine *et al.*, 2001 and Ostfeld *et al.*, 2001). So far there have been no universally accepted performance measures to quantify the consequences of extreme events. However, the measures proposed in the literature are capable of capturing different aspects of the behaviour of WDS during failure events. These are discussed in the next section.

Walski (1984) pointed that reliability based performance measures need to consider the consequences experienced by the consumers. Similarly Ostfeld (2001) mentioned that these measures should be consumer driven and must be able to indicate the required levels of service. Therefore, generally performance measures must reflect the behaviour of WDS from the point of view of consumers. Hence the characteristics of performance measures that represent the behaviour of WDS should also be able to address the following along with considering the reliabilities, availabilities and risk in the system due to failure:

- Extent of the consequence to consumers due to failure.
- Variation in the LOS among consumers during a failure.
- Frequencies of breaching consumers LOS.
- Consumers' failure experience.

Observation of existing performance measures assists in categorising them into three different groups, namely; reliability based measures, availability based measures and risk based measures. Although the three types of measures differ in definition they are interconnected as they all are functions of flows, pressures and time.

Reliability based performance measures indicate the ability of the WDS to function in spite of the possible supply interruption throughout a given time period. Mathematical expressions of these measures are functions of available and required flows in a system or at the nodes of the system. This measure is obtained for failure events occurring throughout a time frame (say 10 years).

On the other hand availability measures indicate the proportion of time when the WDS is not in a failure mode. In other words, availability represents the amount of time the WDS operates with satisfactory LOS. The difference between the reliability and availability measures is that the former is a function of flow ratios whereas the latter is a function of time. However, higher values of reliability measure implies that the system performance is satisfactory and hence the system is available. That is higher reliability values will imply that the WDS is available for longer durations and vice versa.

Risk based performance measures attempt to evaluate the risk of the WDS failing due to a particular failure event within a given time frame. Risk is the complement of the reliability; therefore, a WDS with high risk will have low reliability and as a result low availability.

In a WDS, it is very rare to find any two nodes behaving in similar manner, also evaluating the performance of nodes does not give any indication of the performance of the WDS as a whole. Therefore, performance measures that describe the behaviour of individual nodes as well as entire WDS are needed. Description of each category is given below.

2.3.1 Reliability Based Performance Measures

In the literature, several different definitions of reliability based measures have been proposed. Their definitions are mainly functions of the ratios of available and desired demands at nodes (Tanyimboh *et al.*, 2001; Shamir and Howard, 1981). Furthermore, reliability measures given in the literature covers both nodal and system reliability issues.

Nodal reliabilities evaluate the behaviours of individual nodes during failures and system reliabilities express the system performance. Both nodal and system reliabilities are interdependent. Fujiwara and Ganesharajah (1993); Xu and Goulter (1998) mentioned that there is a continuing uncertainty in the relationships between nodal and system reliability. It has been the practice to indicate the system reliability with a single index along with nodal reliabilities (Bao and Mays, 1990). This is due to the fact that a single system reliability index will not be able to capture the whole picture of the system performance. Tanyimboh *et al.* (2001) showed that the system reliabilities can be given by demand weighted means of nodal reliabilities.

Bao and Mays (1990) proposed performance measures based on probability of sufficient supply. They specified nodal and system reliability measures to assess the performance of the water distribution system.

Nodal reliability R_n was given as the probability that a given node receives sufficient flow rate at the required pressure head. In other words the nodal reliability is the joint probability of flow rate and pressure head being satisfied at the given nodes. But it is difficult to determine the joint probability of the flow and pressure head being satisfied as both of them are interdependent. In order to rectify this issue, Bao and Mays (1990) used the conditional probability in terms of the pressure head, provided that the water demand has been satisfied. Mathematical expression for the nodal reliability is given as the probability that the supplied pressure head H_s at the given node is greater than or equal to the required minimum pressure head H_d^l. This is given below in equation 2.1.

$$R_n = P\left(H_s > H_d^l \setminus Q_s = Q_d\right) = \int_0^\infty f_s(H_s)\left[\int_0^{H_s} f_{dl}\left(H_d^l\right)dH_d^l\right]dH_s \qquad (2.1)$$

Where $f_s(H_s)$ is the probability density function of the supplied pressure head and $f_{dl}\left(H_d^l\right)$ the probability density function of the minimum pressure head.

Considering both upper and lower bounds of the nodal heads (H_d^u and H_d^l), the nodal reliability is expressed as:

$$R_n = P\left(H_d^u \geq H_s \geq H_d^l\right) = \int_{H_{dl}}^{H_d^u} f_s(H_s)dH_s \qquad (2.2)$$

Bao and Mays (1990) proposed to represent the composite effect of the nodal reliabilities by defining system reliability measures. They provided three different expressions for the system reliability as functions of the nodal reliabilities that are given below:

- The system reliability R_{sm} is expressed as the minimum of the nodal reliabilities:

$$R_{sm} = \min\left(R_{ni}\right) \qquad (2.3)$$

Where R_{ni} is the nodal reliability at node, i is the node number

- System reliability R_{sa} is expressed as the arithmetic mean of the nodal reliabilities.

$$R_{sa} = \frac{\sum_{i=1}^{N} R_{ni}}{N} \qquad (2.4)$$

Where N is the number of nodes in the system.

- System reliability R_{sw} is expressed as the supply weighted mean of the nodal reliabilities.

$$R_{sw} = \frac{\sum_{i=1}^{N} R_{ni} Q_{si}}{\sum_{i=1}^{N} Q_{si}} \qquad (2.5)$$

Where Q_{si} mean value of water supply at node i.

The nodal reliability measure proposed by Bao and Mays' is the probability of the pressure head being within the upper and lower bounds of the nodal heads. This would only imply the number of times a node being in a satisfactory or failed condition during a given simulation period. In other words the performance of the node is expressed as the frequency of pressure violations at the node. This does not provide any indication of actual consequence at the node. For example during an extreme event, there will be a reduction in flow into nodes due to the loss of water from WDS, as a result a flow shortfall. Moreover, the extent of the consequences due to such flow shortfalls is not reflected.

Out of the three system reliability measures the first two are the minimum and average probabilities of nodes satisfying the pressure constraints. These are meant to indicate lower bound and the average values of the system reliability respectively. It should be noted that representing the system reliability using the lowest value of the nodal reliability may indicate a distorted picture of the system as the reliability of the entire WDS is represented by the node with the lowest reliability, this is an extremely conservative approximation. In an event where the reliabilities of the majority of the nodes are considerably high (frequency of pressure violations are low), the reliability indices will still show that the system operate with low reliability (or with a high number of pressure violations).

Equally representing the system reliability using arithmetic mean of the nodal reliabilities is also not appropriate as there may be considerable variations in the performance among nodes i.e. arithmetic means are sensitive to extreme values. Still this measure gives a better picture than the earlier one as the contribution from each and every node is considered in the derivation of the system reliability. An important point to note is that each and every node in a WDS has different characteristics in terms of demand, number of consumers etc., therefore, a similar pressure violation at two different nodes may result in different in the extents of consequences depending on the characteristics of the node. This fact is not included in the arithmetic mean. One way to include nodal characteristics with the reliability may be to assign weights to nodes.

The third system reliability expression proposed by Bao and Mays' is the flow weighted mean of nodal reliabilities. The weights corresponding to the nodal characteristics are represented by average nodal flows. This measure is the most appropriate of the three system reliability expressions as it takes account of characteristics of nodes as well as their individual reliabilities.

Khomsi *et al.* (1996) developed similar performance measures to that of Bao and Mays (1990) to analyse both the nodal and system performance of the water distribution system. They defined an availability measure to assess the performance of the node and a reliability measure for the system.

Khomsi *et al.* (1996) defined the nodal availability as the probability of a given node receiving sufficient supply at or above a minimum pressure. The nodal unavailabilities are obtained as given below.

For network without failure;

$$F(i,m) = PKLoad(t) * PNetwork \qquad (2.6)$$

Where $F(i,m)$ is the nodal unavailability, $PNetwork$ is the probability of no pipes being out of action, m is an index for counting violations of minimum pressure, i is node number, $KLoad(t)$ is the demand factor for time t and $PKLoad(t)$ is the probability corresponding to the demand factor $KLoad(t)$.

For a reduced network (with failure);

$$F(i,m) = P_{pipe}(k) * PKLoad(i) \qquad (2.7)$$

Where $P_{pipe}(k)$ is the probability of pipe k failure.

Reliabilities of individual nodes are given as the total nodal availabilities;

$$R_{ni} = A(i) = 1 - Fn(i) \qquad (2.8)$$

Where $Fn(i) = \sum_{m=1}^{M_{\max}} F(i,m)$, $M_{\max}$ is the number of pressure violations and $A(i)$ is the nodal availability.

The reliability of the system has been expressed as the demand weighted means of the nodal reliabilities.

$$R_S = \sum_{i=1}^{N} [R_{ni} * Q_{ext}(i)] / \sum_{i=1}^{N} Q_{ext}(i) \qquad (2.9)$$

Where $Q_{ext}(i)$ is the time-averaged demand at node i; and R_S is the system reliability.

The nodal availability and the reliability expressed above represent the probability of the node being available during a period of time. The difference between these measures and that of Bao and Mays (1990) is that the nodal availability is based on probability of sufficient supply above a minimum pressure whereas, the nodal reliability is a function of probability of pressure head satisfying the minimum required value. The additional feature in Khomsi's definition is that they incorporated the variable nature of the nodal demand by introducing demand factors. However, like Bao and Mays' performance measures, these also do not indicate the magnitude of nodal reliability in terms of consequences of an extreme event. The shortcomings associated with Bao and Mays are equally applicable to the measures proposed by Khomsi *et al.* (1996).

System reliability proposed by Khomsi *et al.* (1996) is similar to that of Bao and Mays' third system reliability measure. Both measures are supply weighted means of nodal reliabilities, therefore, the criticisms of Bao and Mays is also applicable to this situation. The system reliability measure like the nodal reliabilities does not indicate the severities and actual shortfalls in flows during failure situations, but rather provides an index based on probability of sufficient supply at the nodes.

Shamir and Howard (1981) outlined the considerations involved in determining the reliability of water distribution systems. They defined three performance measures namely; the discharge reliability factor, the volume reliability factor and the overall reliability factor. The proposed performance measures were based on short falls of total volume and supply rate. The overall reliability factor was defined as the average of discharge reliability factor and volume reliability factor which are defined below.

Discharge reliability factor is defined as:

$$RC = 1 - \left(\frac{C}{CT}\right)^n \qquad (2.10)$$

Where RC is the discharge reliability factor, C is the capacity rate in units of discharge lost, CT is the total capacity required and n is an integer.

Volume reliability is defined as:

$$RV = 1 - \left(\frac{V}{VT}\right) \qquad (2.11)$$

Where $V = C * D$, RV is the volume reliability factor, V is the volume shortfall during a single failure or an entire time period, VT is the total volume required, D is the time required for repair and restoration.

Overall reliability factor RF is given as;

$$RF = \frac{RC + RV}{2} \qquad (2.12)$$

Also

$$RF = 1 - \frac{(C/CT)^n + (C/CT)}{2} \qquad (2.13)$$

In developing these measures Shamir and Howard considered the demand as a random variable; as a result the reliability factor becomes a random variable. The measures proposed by Shamir and Howard are applied for lumped (demand and supply) model, they did not consider individual areas of networks affected due to extreme events. However, these reliability expressions are equally applicable to individual nodes. Shamir and Howard varied the values of the exponent from 0 to 5 and found the values of n greater than 1 caused the discharge reliability factor to decrease rapidly when C approaches CT and for values of n below 1, the discharge reliability factor was found to decrease rapidly for small values of C. If the exponent becomes unity, discharge reliability factor, volume reliability factor and the network reliability factor will be identical.

In the expressions given above discharge reliability factor has a power relationship whereas the volume reliability factor is a linear function. The variables in both the relationships are same (C, CT) therefore, the difference between discharge reliability factor and the volume reliability factor is the exponent. However, Shamir and Howard did not give any information on how the values for the exponent were evaluated. From the expression of reliability factors, it can be seen that the exponent depend on the characteristics of the distribution system. The discharge, volume and overall reliability factors will be represented by positive indices, but it is not very clear how these indices can be interpreted to reflect the performance of the WDS during extreme events. All three reliability factors that have been discussed above are not consumer driven measures (i.e. they do not consider the effect of failure on the consumers) but only indicate the system performance.

Fujiwara and De Silva (1990) developed system reliability measures for water distribution system as a function of total minimum shortfalls in flows. They defined the system reliability R_S as the complement of the ratio of the expected minimum total shortfall in flow to the total demand.

$$R_S = 1 - \sum_{j=0}^{nl} p(j)\left(1 - \frac{F_j^*}{d}\right) \qquad (2.14)$$

Where $p(j)$ is the probability that only link j fails while all other links operate, F_j^* is the maximum flow during the failure of link j, d is the total demand of the system and nl is the number of links.

The maximum flows in the links of the system are estimated using a maximisation algorithm. The system reliability obtained by this measure will be an upper bound as the reliability is a function of minimum total shortfall. This measure takes all the failure events into account when evaluating the performance measure. Therefore, the system performance due to a single failure is not known.

Gupta and Bhave (1994) proposed performance measures as functions of shortfalls of nodal outflows but slightly differed from other measures as Gupta and Bhave's measures do not incorporate probabilities of component failures into their formulation. These measures cover both the node level and system level reliability. The three indices given are: the node reliability factor, the volume reliability factor and the network reliability factor.

The node reliability factor is defined as the ratio of total volume of water supplied to volume required for the entire duration of the analysis and is given by:

$$R_{ni} = \frac{\sum_s V_{is}^{avl}}{\sum_s V_{is}^{req}} \qquad (2.15)$$

Where R_{ni} is the node reliability factor, V^{avl} is the available volume, V^{req} is the required volume, i is the node number, s is the state of the node.

This factor considers all the states during a failure event when evaluating the reliability factors; for example during a pipe failure event, all three states: the failure state (dynamic); the isolation state (repair period) and the normal state (time after the repair) are considered. Therefore, this measure enables to capture the entire picture during the failure event.

The volume reliability factor is defined as the ratio of the total volume of water supplied to the volume required for the entire network for all states during the period of analysis. This is also related to the node reliability factor as the cumulative total of node reliability factor gives the volume reliability factor. In other words this can be called the system reliability factor.

$$R_V = \frac{\sum_s \sum_i V_{is}^{avl}}{\sum_s \sum_i V_{is}^{req}} \qquad (2.16)$$

Where R_V is the volume reliability factor, V^{avl} is the available volume, V^{req} is the required volume, j is the node number, s is the state of the node.

The node factor F_n is a measure indicating the performance of all the nodes and defined as the geometric mean of the node reliability factors:

$$F_n = \left(\prod_{i=1}^{N} R_{ni} \right)^{1/N} \qquad (2.17)$$

In this measure all the nodes have been allocated the same weighting and also this measure can be interpreted as another way of expressing the system reliability. Compared to the volume reliability factor, the node factor will be smaller due to the multiplication of the node reliability factors. Also a node with zero reliability will result a zero node factor whereas volume reliability factor will still have a value greater than 0.

Network reliability factor described by Gupta and Bhave (1996) evaluates the reliability of the system as a whole and is defined as:

$$R_{nw} = R_V F_t F_n \qquad (2.18)$$

Where R_{nw} is the network reliability factor, F_t is the time factor (see availability measures), F_n is the node factor and R_V is the volume reliability factor. The network reliability factor is a function of F_t, R_V and F_n therefore, the network reliability factor will have all the weaknesses of the above factors.

Tanyimboh *et al.* (2001) proposed nodal and system reliability measures taking into account the availability of the components in the distribution system. They suggested that the state of the system, whether it is in an operational or failed mode is the prime factor dictating the quantity of water delivered to the consumers. Clearly the status of the system depends on the availabilities of the component. A reduced state occurs when a component is unavailable to the system due to a failure event (such as pipe burst, pump outage) or repair and maintenance activity. Tanyimboh *et al.* (2001) defined that probability $P(\phi)$ that all the pipes are available is given by:

$$P(\phi) = \prod_{j=1}^{nl} a_j \qquad (2.19)$$

Where a_l is the probability that link l is available, nl is the number of links. If there are NS subsets with NC components in each set. Tanyimboh *et al.* (2001) again proposed that probability of a subset of link S_j, and only that subset is unavailable is given by:

$$P(S_j) = P(\phi) \prod_{j=S_j}^{nl} \left(\frac{u_j}{a_j} \right) \quad \text{for all } S_j \qquad (2.20)$$

u_l is the unavailability of a component and pipe availability is generally given by the ratio of mean time between failure and mean time between failure plus the mean time between repair (Cullinane *et al.*, 1992). This can be expressed as a function of pipe diameters as follows:

$$u_j = \frac{0.01873D^{1.462131}}{0.000294D^{0.285} + 0.01873D^{1.462131}} \qquad (2.21)$$

D is the diameter of the pipe in millimetres.

The nodal reliability of the system is defined as the ratio between the available and desired flow at the node. Nodal reliability when S_j is unavailable is given by:

$$r_i(S_j) = \frac{Q_i(S_j)}{Q_i^{req}} \quad \text{for all } S_j \text{ and } i \qquad (2.22)$$

$r_i(S_j)$ is the reliability, $Q_i(S_j)$ flow available at node i when S_j is unavailable. Considering only one and two component subsets the nodal reliability is given by:

$$R_{ni} = \frac{1}{Q_i^{req}}\left(P(\phi)Q_i(\phi) + \sum_{l=1}^{nl} P(l)Q_l(l) + \sum_{l=1}^{nl}\sum_{m:m>l} P(l,m)Q_i(l,m)\right) \qquad (2.23)$$

$P(l)$ is the probability that only pipe l is unavailable, $r_i(l)$ is the reliability when pipe l is unavailable, $Q_i(l)$ is the flow when pipe l is unavailable and $P(l,m), r_i(l,m)$ and $Q_i(l,m)$ corresponds to the unavailability of two components.

When there is an unavailability of more than two components the formulation for the reliability becomes

$$R_i = P(\phi)\left(\sum_{i=1}^{NS}\left(r_i(S_j)\prod_{l\in S_j}\frac{u_l}{a_l}\right) + r_i(\phi)\right) \quad \text{for all } i \qquad (2.24)$$

System reliabilities are obtained by demand weighted means of nodal reliabilities and the general expression for the system reliability or the network reliability R_S of the network as a whole is given by

$$R_S = P(\phi)\left(\sum_{i=1}^{NS}\left(r(S_j)\prod_{l\in S_j}\frac{u_l}{a_l}\right) + r(\phi)\right) \qquad (2.25)$$

$r(S_j) = \dfrac{Q(S_j)}{Q_i^{req}}$ is the system reliability when S_j is unavailable

The above measures by Tanyimboh *et al.* (2001) are expected values of the observed and desired flows at nodes during the failures of a particular component. This reliability formulation has the ability to incorporate more than one simultaneous failure event. These measures are developed only to accommodate component failures, therefore, modifications need to be made to include failure events other than component failures, for example failure due to demand exceedence (during peak demand situations) can be incorporated by including the probabilities of demand exceedence in the WDS in place of the probabilities of component failure.

Tanyimboh's measures estimate the nodal and system reliabilities based on expected shortfalls. That is for a single component failure event, Tanyimboh considers the ratios of available and required flows at the node during no failure and also due to the component failure.

Ostfeld *et al.* (2002) proposed reliability measures based on the nodal demands and the durations of no failure in the system. These measures are very similar to that of Gupta and Bhave (1994). Ostfeld *et al.* (2002) defined two measures (fraction of delivered volume and fraction of delivered demand) particularly to evaluate the levels of service in terms of supply.

Fraction of delivered volume is defined as the ratio of the sum of the total volumes delivered to a consumer node i and the sum of the total volumes requested by the consumer node at all simulation runs.

$$FDV_i = \frac{\sum_{j=1}^{N} V_{j,i}}{V_T} \quad \text{for all consumer nodes } NN \qquad (2.26)$$

Where FDV_i is the fraction of delivered volume at node i, NN is the number of consumer demand nodes, N is the number of simulation runs, $V_{j,i}$ is the fraction of volume supplied to node i at all runs, V_T is the total volume supplied at all runs.

This measure considers the entire duration of the operation therefore, only the overall performance of the node is identified, but the performance of the node during a particular failure event is not reflected. This can be easily achieved by performing the simulation only for the particular event, provided that the time of failure and the duration of failure are known. The measure only indicates the localised reliability (nodes) but does not consider the system wide reliability.

Reliability based measures discussed above have been developed keeping in mind, the need to identify the ability of the WDS to survive a particular failure event. Both the nodal and the system reliability measures have values between 0 and 1. The information that can be obtained from these measures is the expected demand shortfall values and the probabilities of WDS receiving sufficient supply. Although such information is helpful in understanding the behaviour of the system, lack of the ability of these measures to inform the consumer based issues such as frequency and extent of consumers' failure experiences warrants further investigation into developing new measures.

2.3.2 Availability Based Performance Measures

The availability measures express the duration of a node or system experiencing acceptable LOS during a failure event in the WDS. Cullinane *et al.* (1992), Gupta and Bhave (1996) and Ostfeld *et al.* (2001) are a few who employed availability measures to assess the performance of WDS.

Cullinane *et al.* (1992) introduced availability measures to determine the performance of water distribution systems. They suggested that availability measures are more appropriate for the water distribution system than the reliability measure as the components in the system are repairable.

They devised the availability measure into two as the hydraulic and the mechanical. The Hydraulic availability is concerned with the quantity of water delivered, the residual pressure at the outlets, time of supply, and the location within the system to which the water is delivered. On the other hand, the mechanical availability is concerned with the availability of the water distribution system components.

Cullinane *et al.* (1992) defined the hydraulic availability of a water distribution system as the ability of the system to operate with an acceptable level of interruption in spite of abnormal conditions. In other words availability is the percentage of time that the demand can be supplied at or above the required residual pressure.

The hydraulic performance at critical locations in the distribution system may be more important than the average system availability as a result of the spatial and temporal distribution of demands in the system. However, the overall average system availability may be an important indication of performance therefore, any unified procedure for evaluating the WDS availability should be capable of computing the availability at a point and the average system availability.

The nodal availability, $A(i)$ at node i, is given as the percentage of time that the pressure at the node is greater than a preset required value, which is stated as:

$$A(i) = \sum_{i=1}^{ts} \frac{av_i t_i}{T} \qquad (2.27)$$

The system reliability A is given as the average of the nodal availabilities in the system.

$$A = \sum_{j=1}^{NN} \frac{A(i)}{NN} \qquad (2.28)$$

Where $A(i)$ is the nodal availability at node, t_i is the length of time periods, av_i is the availability during time period i, ts is the number of time periods at which node is available, T is the total time of simulation and NN is the total number of nodes.

The two equations 2.27 & 2.28 above assumes that the components are perfectly reliable, this is far from the reality therefore, Cullinane *et al.* (1992) combined the mechanical availability and the hydraulic performance using expected value analysis. Hence the nodal availability can be stated as;

$$AE_{il} = R_l\left(A(i)_l\right) + Q_l\left(A(i)_{ll}\right) \qquad (2.29)$$

Where AE_{il} is the expected value of nodal availability considering link l, R_l is the probability that link l is operational, Q_l is the probability that link l is non operational, $A(i)_l$ is the nodal availability with link l operational and $A(i)_{ll}$ is the nodal availability with link l non operational.

Previous works by Su *et al.* (1987); Goulter and Coals (1986) and Cullinane *et al.* (1992) proposed a discrete, zero-one relationship between the availability during a time period (av_i) and the pressure. Using this relationship, availability during a time period i can be expressed by the following mathematical relationship;

$$av_i = 1 \qquad \text{for } h_{it} \geq PR \qquad (2.30)$$

$$av_i = 0 \qquad \text{for } h_{it} < PR \qquad (2.31)$$

Where av_i is the availability during time period i, h_{it} is the residual pressure at node i during time period t, PR is the required pressure.

The discrete approach assumes that the availabilities of nodes are zero below the required pressure, for example if the required pressure is 20m, and the available pressure is 1m, the availability value will be zero, when the pressure becomes 19.9m still the availability value will be evaluated as zero.

When supplying to a UK household where there is an over head tank (OHT), the head at the stop tap should be higher than the minor losses and the height of the OHT, a lower head will result in water not reaching the tank. Similar situations can be seen with the stand pipes. In these situations the discrete approach of the availability can be applied. However, it is important to evaluate the minimum required pressure accurately. In systems where the minimum required head and the desired heads are not defined, the discrete availability relationship may not accurately represent the real situation within the range of minimum and desired head. In such situations a continuous availability function can be used.

Cullinane *et al.* (1992) proposed a continuous availability function based on the normal distribution function to incorporate the partial failure situations (Figure 2.1) in water distribution systems. This approach is more appropriate as it determines the availabilities for a range of residual pressures.

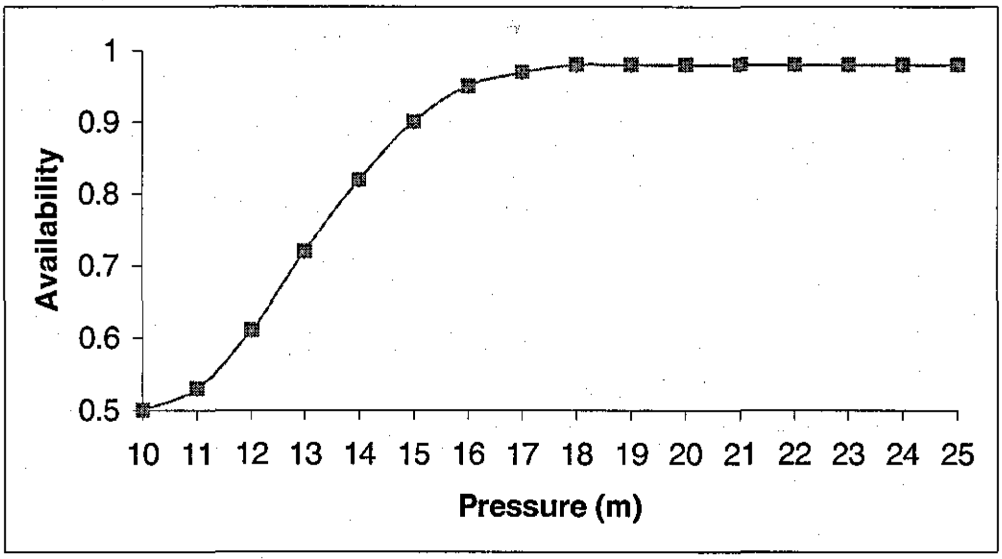


Figure 2.1: Continuous nodal availability

The main feature of the availability measure is that its ability to evaluate the availability of the partially operational nodes. It does not quantify the extent of the consequence of an extreme event in terms of flow shortfalls but only suggest the system uptimes. The system availability index is evaluated by giving similar weightings to all the nodes. This is not appropriate as the performance of nodes differ depending on factors like the consumer behaviour, demand and the location. Moreover, this measure fails to mention impact of the WDS down times on the consumers.

Gupta and Bhave (1996) proposed "Time Factor" along with other reliability measures. This measure is synonymous with Cullinane's availability measure as it indicates the period during which the WDS is at operational state.

The time factor for a distribution network is given as:

$$F_t = \frac{\sum_{s}\sum_{i=1}^{NN} a_{i,s}}{NN\sum_{s} t_s} \qquad (2.32)$$

t_s is the duration of time period s, NN is the total number of demand nodes, $a_{i,s}$ is the performance rating of node i during the time period s. Which is defined as $a_{i,s}=1$, if the ratio of flow delivered to the flow required $\left(Q_{i,s}/Q_{i,s}^{req}\right)$ is equal to or greater than an acceptable value (0.5 for example), $a_{i,s}=0$, otherwise.

Gupta and Bhave (1994) did not provide any insight into how to rationally decide on the acceptable value of the ratio of flow delivered to the flow required. Therefore, the evaluation of the performance rating is arbitrary and depends on the experience of the individuals.

The time factor is an arithmetic mean of the performance rating and it has the same weightings assigned to all the nodes. This is not acceptable, as different nodes will have different performance levels. The discrete relationship of the performance rating will have the shortcoming of the discrete availability discussed above. This can be rectified by having a continuous relationship as shown in Figure 2.1.

Ostfeld *et al.* (2001) developed "the Fraction of Delivered Demand" measure similar to that proposed by Gupta and Bhave (1996). The fraction of delivered demand is a measure that indicates the availability of the node during the operation of the distribution system. This measure is defined as the ratio of the sum of all the time periods at all simulation runs for which the demand supplied at a consumer node j is above the demand factor (i.e. the system is up) and the total number of simulation runs multiplied by the demand cycle.

$$FDD_i = \frac{\sum_{i=1}^{N} t_{i,j}}{N * T} \quad \text{for all } NN \qquad (2.33)$$

Where FDD_i is the fraction of delivered demand at node i, N is the number of simulation runs, T is the duration of each run, $t_{i,j}$ is the total duration at run j at node i for which the demand supplied is above the demand factor (i.e. the system is up).

The short coming with the fraction of delivered demand is similar to that of the other availability measures. They are only capable of indicating the average system up times and do not provide details of the performance in terms of demand.

The availability measures, like the reliability, mainly focus on the performance of the system. They only indicate the times at which the system is operational and overlook the experiences and consequences faced by consumers resulting from the failure events. Knowledge of system uptimes is a good indicator of the performance of the WDS, however, it lacks detail on satisfying consumer demand at the nodes and the frequency of demand shortfall.

2. 3. 3 Risk Measures Based on Simulation Method

Risk measures in WDS try to quantify how likely the system is susceptible to failure and what would be the consequence corresponding to such a failure event. Risk is the complement of reliability. Germanopoulos (1988) and Vairavamoorthy (1990) introduced performance measures based on probability analysis to evaluate the consequences in WDS during a failure event. The measures indicated the probability of a failure event exceeding certain duration with a particular frequency. The proposed measures are given below.

$$\Pr(r,T) = \frac{(T/\mu)^r \exp(-T/\mu)}{r!} \qquad (2.34)$$

Where $\Pr(r,T)$ is the probability of r failures in time T, μ is the expected period of time between successive failure occurrences.

The probability of the duration t of one failure event being greater than a given time t^* is given by:

$$\Pr\left(t > t^*\right) = \exp\left[-\left(t^* - c\right)/tr\right] \qquad (2.35)$$

Where tr is the expected duration of repair is, c is the period of time between failure occurrence and beginning of repair.

The above two distributions can be combined to give the probability of occurrence of a failure event of duration greater than t^*, which is given by:

$$\Pr\left(t > t^*, n, T\right) = \frac{\left(T/MF\right)^n \exp\left(-T/MF\right)}{n!} \qquad (2.36)$$

Where $\Pr\left(t > t^*, n, T\right)$ is the probability of duration t of n failure event in time T greater than duration t^*, MF is the mean time between failure events of duration greater than t^*.

These measures provide the probabilities of failure events exceeding a prespecified duration. In order to apply the above risk measures to a WDS, data on pipe failure and repair are required. Obtaining this type of information is a tedious task as most of the WDS have ageing assets for which the water utilities do not have complete failure or repair records. None of the above mentioned expressions of risk have any term to reflect the demands of WDS hence do not explicitly indicate the shortfalls in demand associated with the failure, however, they can be related with these measures by retrospectively evaluating the demand shortfalls. Furthermore, the above risk measures fail to represent the consequences associated with the consumers as a result of the failure.

Unlike the reliability and the availability measures, risk measures do not expose details of the demand shortfalls and failure experiences of the consumers. They rather inform on the performance of the system. Therefore, performance measures that reflect consumer failure experiences need to be developed.

2.4 Performance Measures Used in the Industry

The water companies and regulatory bodies have long recognised the importance of developing measures to quantify the WDS behaviour and to assess the consequences caused by the failure events. Over the past few years, several measures that are capable of predicting the behaviour of the WDS have been proposed in the literature, but applicability of those measures in the industry depends on the ability of operationalising them.

Specified LOS requirements for water companies in England and Wales are defined as 10m static pressure at the consumer's stop tap or 9 l/minute flow from the kitchen tap (OFWAT, 2005). This pressure is sufficient to lift the water to the second floor of a household.

OFWAT (2005) specified benchmark performance assessment criteria for WDS is an event where the pressure at the consumers stop tap falling below the minimum 7m over one hour period for more than twice in four weeks.

The bench mark performance assessment criteria can be related to the availability and the risk measures discussed above in this chapter. The availability can be determined by evaluating the time duration for which the households experience pressure at least 7m. The risk associated with the WDS can be determined by evaluating the probabilities of more than two failure events of duration one hour occurring within four weeks.

The bench mark criteria suggest that it is allowable to have two failures every month where the consumers experience static pressure below 7m through duration of more than one hour. Also this implies that failure events of duration less than one hour are not considered. The major shortcoming in this measure is that it does not account for the intensity of failure in terms of shortfalls, also severity faced by the consumers if the failure occurs during peak demand periods.

Although these measures provide some form of indication of the levels of service provided by the water companies, the duration of lack of supply and how the system respond to the loss in levels of service are not reflected. Therefore, it is essential that appropriate performance measures need to be applied in the water industry to represent the behaviour of WDS.

In the event of operationalising the performance measures in WDS, it is of interest to know the local as well as global effects on the system due to failures in the WDS. This warrants the introduction of measures that indicate the behaviour of both the system and that of consumers.

System performance measures will assist in comparing the WDS under different operational conditions while the measures indicating the local performance will show the impact of different condition on different parts of the network and the consumers.

2.5 Criticisms of Existing Performance Measures

In this chapter existing performance measures were reviewed and their applicability to WDS analysed. The existing measures have been categorised into three types depending on the definition and the information that is expected to obtain from the measure. Most of the reliability, availability and risk measures proposed in the literature, which have been discussed above provide useful information such as percentage of supply shortfalls in WDS, system uptimes and probabilities of failure events occurring in a particular period of time.

The performance measures that have been described in the literature are very useful in understanding the behaviors of WDS during extreme situations. However, there are a number of limitations associated with them. The first limitation is the performance measures themselves and how they have been defined and that there is some concern about how well these performance measures really reflect the levels of service that consumers experience.

The reliability definitions that are most favoured in the literature are based on the nodal performance (Tanyimboh *et al.,* 2001), due to the fact that the reliability index can be related to WDS performance. Definitions that are based on probabilities give good indications of the reliability but lack the ability to relate the consequence of extreme events in terms of flow and pressure with it.

The reliability of a WDS is generally looked at two different levels; the node level and the system level. The node level reliability expresses the ability of an area covered by the WDS node to withstand the impact of extreme events, thus expressing the localised performance. On the other hand, system reliability indicates the collective performance of nodes in terms of reliability.

Nodal reliabilities are usually defined as functions of demand shortfalls (Gupta and Bhave, 1996; Tanyimboh *et al.,* 2001; Tabesh *et al.,* 2004). This measure expresses that a particular node will function with certain reliability (say 0.5) throughout a period of operation (say 10 years) due to failures or extreme events in the WDS. This suggests that at least 50% of the demand is satisfied at that node during extreme events. However, it does not clarify which of the scenarios mentioned below is referred to:

- All the consumers in the node receive at least 50% of the demand through out the failure.
- Only 50% of consumers served by the node receive 100% supply and remaining consumers receive nothing.

Assuming that the consumers have similar demand characteristics.

Both of the above scenarios will result in the same reliability index but extents of consequence experienced by the consumers differ greatly between the two situations. Therefore, the reliability index is not sufficient to express different scenarios that might occur in the system.

Reliability of a WDS is dependent on factors such as the magnitude of failure event, the frequency of failure, the duration of failure and the duration of repair. A large failure of a shorter duration and a small failure of a considerably larger duration can result in same reliability factor for the WDS. However, the impact of larger failure may be high on the consumers as a result of loss in large quantities of water whereas small failure will have not so significant impact as the rate of water loss is low. Such events are insensitive to the reliability indices.

The system reliability is meant to indicate the reliability of the entire WDS to failure events. This is evaluated by averaging the nodal reliabilities (Gupta and Bhave, 1996), and in some instances nodal demands are assigned as weights to reflect the individual contribution of nodes (Tanyimboh *et al.*, 2001). The latter method is more appropriate than the former one, however, selection of nodal demand ratios as weights does not reflect the impacts of failure of the consumers rather indicates an overall performance of the node. Therefore, appropriate weights that indicate the impacts of the nodes need to be introduced in evaluating system reliability. Furthermore, system reliabilities alone will not give a clear picture of the WDS. For example a reliability value of 0.5 can suggest that either 50% of the nodes are receiving 100% of supply while the remaining nodes operate in a complete failure state or all the 100% of the nodes operate at 50% efficiency. Therefore, both nodal and system reliabilities need to be looked at simultaneously.

The nodal and the system availabilities are meant to inform the durations at which demand is supplied to the systems at a pre specified pressure. The approaches that have been applied so far do not clearly indicate how to determine the minimum required pressure above which the nodal availability is 1. This type of availability is not applicable to partial failures. However, continuous availability measures can be used to overcome this shortcoming. Here the pressure range at which the availability is between 0 and 1 depends on the mean and variance of the pressure at node.

The risk based measures discussed in the review are capable of informing the probabilities of an extreme event with a certain consequence occurring in a given duration. In other words risk based approach explores the frequency of failures which causes the system to meet a certain LOS in a given period of time. This measure enables to identify the most critical component of the system. The information retrieved from this measure depends on the accuracy of the field data on the component failure and the repair durations for each component.

The investigation of the existing performance measures reveal that they mainly focus on levels of service based on the flow ratios. They do not give specific information on the impacts of failures at the consumer nodes and the system, such as:

- The uniformity of demand shortfalls among the nodes; this will indicate the relative performances of the nodes during failure events.
- The nodes that satisfy a pre specified percentage of demand during extreme events; suggesting the extent of failures within the WDS.
- The number of times a pre specified demand is breached due to failure during given span of time (say 10 years).
- The failure experience of the consumers as a result of their internal piping condition.

The issues mentioned above will provide better insight into the performance of the WDS as well as into the impact of failure on the consumers. Therefore, performance measures that embrace the criticisms of the existing measures and give better insight into the behaviour of WDS are needed.

2.6 Deriving New Measures

The above review on the performance measures revealed that there are some issues which need to be addressed. The focus of this section is to develop performance measures which address the concerns raised above that would help to give better insight into the behaviour of the WDS performance during extreme events. The primary difference between the existing measures and the proposed ones is that the proposed measures focus on the extent of the impacts of failure at the nodes and the system as a whole.

The performance measures proposed in this section have been developed using existing definitions as well as the performance indices employed in the other fields of engineering, irrigation engineering in particular. The derivations of the proposed performance measures are given below.

2.6.1 Equity

The primary performance measure that is proposed in this section to address the issue of supply uniformity is called the equity. This is defined as "*the complement of the average variation of the actual and the mean demand allocation ratios of flows at nodes*". The demand allocation ratio represents the ratio of flow at a particular node and the cumulative flows of the entire nodes in the WDS.

Equity represents the uniformity of water supply among the consumers in a WDS. This measure indicates the collective degree of variation in the nodal flows. The basis for the equity performance measure is derived from irrigation engineering, where similar measures have been used to evaluate the equitable supply of water to the farmers during water scarce situations. In order to be able to apply the equity measure to WDS, parallels must able to be drawn between the two systems.

There are very close similarities between the WDS and irrigation systems with respect to water supply. Important similarities corresponding to the equity performance measure are listed below.

- Both systems use links to transport water (canals in irrigation and pipes in water distribution).
- Destination of the water supply is the consumer nodes (farms or lands in irrigation, and demand nodes in water distribution).
- Water demand in the nodes depend on various factors (size of land and types of crop etc., in irrigation whereas type and number of consumers in water distribution).
- Flows to nodes during water scarce situations become inequitable in both systems.

These similarities of both system permits to translate the performance measures used in irrigation system to water distribution systems. Equity in irrigation depends on planned and delivered resources of water to the farms or irrigable lands (Gorantiwar and Smout, 2005). Therefore, the translated definition to water distribution will depend on the actual and desired demands at the nodes. The mathematical description of equity applicable to WDS can be given as:

$$AR_i = \lambda_a / \lambda_d \qquad (2.37)$$

Where AR_i is the allocation ratio for node i, $\lambda_a = \sum_T ad_i \Big/ \sum_T \sum_{i=1}^{n} ad_i$, $\lambda_d = \sum_T d_i \Big/ \sum_T \sum_{i=1}^{n} d_i$

Equity of the WDS is given by

$$E = 1 - \left[\sum_{i=1}^{n} \left[(AR_i - \overline{AR})^2 \right]^{1/2} \Big/ n\overline{AR} \right] \qquad (2.38)$$

ad_i and d_i are the actual and desired inflows to the ith node in the system. AR_i is the allocation ratio for the ith node, $\overline{AR}$ is the average of the allocation ratios, T is the simulation period, n number of nodes.

This measure only indicates the degree of variation among the nodal inflows. Higher equity indicates less variation in the actual and desired flow ratios at nodes. An equity value of 1 indicates that the ratio of the actual and the desired flow at all the nodes are the same. In other words all the nodes have the same percentage of flow shortfall. Higher equity does not necessarily mean that the WDS is operating with a satisfactory level of service. If there is a satisfactory level of service, the equity will be high, as all the nodes will be receiving their allocated or required flows. Therefore, to understand the complete picture of the WDS other measures that are described below must be employed in conjunction with equity.

The equity measure in WDS is used to evaluate the degree of unevenness in the supply to the consumers during extreme situations. This, unlike the system reliability measures, quantifies the variation in the supply at the demand nodes, thus providing an indication of the extent of the difficulties experienced by the consumers at the nodes. This information is helpful in understanding the impact of failures in the WDS which is one of the objectives of performance assessment.

The equity is not only applicable to the primary network of the WDS, but this is equally applicable to the secondary network to evaluate the degree of flow distribution among the consumers. However, the equity measure for the primary network implicitly indicates the variations of inflow to the secondary networks, as these networks receive flows from the primary nodes.

Frequently used measures (the reliability, availability and the risk) do not provide sufficient information about the performance of the WDS. Therefore, measures that complement the already available measures as well as the equity are needed. Such measures are defined below.

2.6.2 Adequacy

Similar to the equity the "Adequacy" measure also has its roots in irrigation engineering and management. From the irrigation perspective, adequacy deals with the water supply for irrigation relative to its demand (Bos *et al.,* 1994; Gorantiwar and Smout, 2005). When translating the adequacy into adapting to WDS, it is very important to consider the parallels between both irrigation systems and WDS. The definition of adequacy proposed for irrigation systems by Oad and Sampath (1995) is equally suitable for WDS.

Oad and Sampath (1995) described the adequacy as "the ability to deliver the amount of water required to meet the farmers demand". This can be converted to a mathematical form by defining the adequacy as the ratio of the actual flow to the desired flow to the farmers. This is identical to the nodal reliability factors defined in the literature review above. However, in the context of WDS, the definition proposed by Oad and Sampath (1995) has been adopted. The definition has been modified to suit WDS and is given below.

The modified definition of the nodal adequacy as used in this section is given as "*the ratio of actual and the desired demand at a particular node through out the simulation period*". The mathematical representation of this definition can be given as:

$$AD_i = \sum_T ad_i \Big/ \sum_T d_i \quad (2.39)$$

Where AD_i is the adequacy at node i, ad_i, d_i are the actual and desired flows at node i and T is the time of the extreme event that causes the reduced levels of service.

This measure is actually describes the percentage of demand satisfied at a node. The aggregated of nodal adequacies is used to describe the adequacy of the system which is defined below.

$$AD = \frac{\sum_{i=1}^{n} AD_i}{n} \quad (2.40)$$

Where n is the number of nodes in the WDS and AD can be taken as the system adequacy.

The aggregated of the nodal adequacies give the percentage of total demand satisfied in the WDS. Therefore, the higher the value of AD, the better the levels of service in the WDS. The desired levels of service will be achieved when AD becomes 1.

Applying both equity and system adequacy measures simultaneously to a stressed WDS will indicate somewhat the whole picture of the situation in the system. Again it is also possible to use these measures to compare the performances of different WDS.

The two performance measures discussed above are not sufficient to understand the behaviour of WDS during extreme situations. Therefore, performance measures that look into different aspects of WDS performance and also the consequences of failure on the consumers are discussed in the following sections. Some of the measures include: severity, node satisfaction, demand satisfaction.

2.6.3 Severity

The performance measures proposed in the previous section consider that each group of consumers or the nodes has the same importance and consequence due to a failure event. However, in real situations this is not the case. The hospitals might be more important and the consequences of failure of supply to them are more severe compared to industries and businesses. The recreation site is important but the consequences of failure of water supply to them may not be severe. The group of consumers having the storage tank can withstand the failure to some extent and hence the consequences may not be as high as when compared to the consequences of a group having no storage. Therefore, it is necessary to include the importance and the consequences of the consumers along with the impact of failure. This section introduces a "severity measure" that takes into account the consumers' importance and consequence simultaneously.

Severity is defined as *the complement of the weighted nodal adequacies.* And the procedure in developing the measure is explained below.

The weight factor that integrates the importance of consumer and consequences of failure is proposed. The approach suggested in the proposed method depends on obtaining the qualitative information from the experts. The qualitative information is in linguistic form, for example:

'importance is extremely low'; 'the consequences are extremely severe' etc. In this case the important task is to determine the number of ranks for qualitative explanation. In this study, based on the discussion with the experts, it is proposed to use 5 number rank systems (Table 2.2). It is expected that the experts assign the rank considering all the aspects including the number of consumers affected, their vulnerability to failure and financial considerations. The numerical equivalent for each rank is obtained by dividing the total scale (0-1) by the number of ranks and multiplying it with its rank number as shown in equation 2.41.

$$N_r = \left(\frac{1}{n_r} r\right) - \frac{1}{2n} \qquad (2.41)$$

Where N_r the numerical equivalent of rank is, n_r is the total number of ranks and r is the rank number.

Table 2.2: Ranks and their numerical equivalent for the proposed qualitative opinions of importance and consequences

Rank	Importance	Numerical equivalent for importance	Consequences	Numerical equivalent for consequences
1	Very low	0.1	Not very severe	0.1
2	Low	0.3	Not severe	0.3
3	Average	0.5	Average	0.5
4	High	0.7	Severe	0.7
5	Very high	0.9	Very severe	0.9

For each node, the weight factor is computed using equation 2.42.

$$W_i = \frac{\sum_{j=1}^{n} P_j C_j}{n_c} \qquad (2.42)$$

Where, W_i is the weight factor for the i th node, P_j is the numerical equivalent for importance for the j th group of consumers at the specified node, C_j is the numerical equivalent for the consequences for the j th group of consumers at the specified node and n_c is the total number of consumer groups.

It is important to prepare proper questionnaires to obtain the appropriate information from the experts on importance and consequences.

The importance and consequences of different types of consumers were obtained by conducting telephone interviews with experts from the water sector. The questionnaires that reflect the importance and the consequence of consumers to failure events were developed and given in Appendix 1.

The experts were asked to comment on the importance of the consumer and the consequence due to failure events in the WDS, taking into account, all the relevant factors affecting the consumers such as; the health, hygiene, financial and the inconvenience.

4 experts from 4 major water consultancies in the UK and an academic from the Loughborough University were interviewed to obtain the consumers failure experience in terms of importance and consequence. The experts were informed of the details related to the water distribution system, consumer distribution and demand categories, before the interviews. The experts were then asked to give their opinion on the severity and the consequences of different types of consumers during failure events.

In reality interviews should be conducted with experts from a variety of stake holder groups (water companies, water authority, public etc.) to obtain the opinions of consumers' severity and consequences during failures. Weights obtained using the data from different stakeholders will provide more realistic picture of the consumers failure experiences. The objective of this section is to demonstrate the applicability of weights in determining the severities of consumers. Therefore, in this research only 5 individuals were interviewed and all of them were considered to be from the water industry, as a result the weights derived were based on the information from one group of stake holders. However, the methodology involved in interviewing and derivation of weights based on the data from different stakeholders is given in Appendix 1.

The proposed severity measure takes the form of;

$$SV_i = W_i \frac{(d_i - ad_i)}{d_i} \qquad (2.43)$$

Where SV_i is the modified performance measure indicating the severity of the node, that includes the importance and consequences of the failure and W_i is the weight factor for this performance measure.

The difference between the performance measure (adequacy) and modified performance measure (severity) would be that the latter one incorporates the importance of consumers and consequences of failure. For example, consider two nodes that have the same value of adequacy. The first node is assigned low value of weight factor meaning that the importance and consumers and consequences of failure are not significant. The second node is assigned a high value of weight factor suggesting that the importance and consumers and consequences of failure are significant. The severity will be higher for the second nodes indicating the importance of this node in the event of failure.

The methodology proposed to include the importance and consequences in this section do not include the uncertainty in obtaining the qualitative information from the experts. The uncertainty aspect can be overcome by using fuzzy based methods to obtain the numerical equivalent for the qualitative information. This is out of the scope of this study, as the purpose in this instance is only to develop the methodology for including the importance and consequences. However, this would form the suggestions for future work.

2.6.4 Demand Satisfaction Ratio

One of the ways of evaluating the consumers' performance is by evaluating the percentage of failure events that will violate a certain pre specified percentage of demand throughout the total number of failure event. The performance indicator that describes this aspect, called demand satisfaction ratio is synonymous with the availability measures proposed in the literature.

Demand satisfaction is a percentage of number of failure events where the consumers will have at least a pre specified amount of demand satisfied. This is given as:

$$DSR_{xi} = \frac{NF - n_{xi}}{NF} \qquad (2.44)$$

Where DSR_{xi} is the demand satisfaction ratio for $x\%$ of the demand to be satisfied for the ith node, n_{xi} is the number of failure events out of total failure events when $x\%$ of the demand is not satisfied and NF is the total number of failure events.

This measure indicates sensitivity of the consumers with respect to the failure events. Higher demand satisfaction ratios mean, failure event does not have high impact on the consumers at the particular node and vice versa.

2.6.5 Node Satisfaction Ratio

The node satisfaction ratio unlike the previous measure, considers individual failure events. It is defined as the percentage of nodes where at least a certain pre specified demand is satisfied during a particular failure event. This measure indicates the percentage of nodes where $x\%$ of the demand is satisfied for a particular failure event j. This is defined as:

$$NSR_{xj} = \frac{(n - d_{xj})}{n} \qquad (2.45)$$

Where NSR_{xj} is the node satisfaction ratio for the demand to be satisfied for the jth failure event, d_{xj} is the number of nodes for which $x\%$ of the demand is not satisfied for the jth failure event and n is total number of nodes.

Node satisfaction ratio directly relates to the number of consumers, who are receiving a certain amount of water during a failure event. This also enables to identify the effects of individual failure events. This is a measure that describes the extent of the system that has been affected due to failure. Therefore, more information about the effect of failure can be obtained.

2.7 Application of Performance Measures

A 30 node network as shown in Figure 2.2 was developed to demonstrate the applicability of the performance measures proposed in this chapter. The network is generated using an ordinance survey (OS) map from a London suburb. The primary network follows the road layout in the OS map. The primary network consists of 40 pipes with diameters varying from 150mm-300mm. The dimensions of the pipes in the primary network are determined by optimising the network using

OPTIDESIGNER (Optiwater, 2003). Secondary networks corresponding to the primary nodes are identified in the OS map and build using EPANET (USEPA, 2000), 28 secondary networks were developed. Details of the network and secondary networks are given in Appendix 1. The analysis of network using different approaches has been discussed in Chapters 4 and 5. However, in this instance the purpose is only to demonstrate the utility of performance measures.

For the purpose of demonstrating the performance measures, the above network is assumed to have only 5 pipe failure events (pipes 1, 3, 4, 8&9) at 10 am in the morning and each failure event was assumed to have failure duration of 3 hours and repair duration of 6 hours. The performance measures corresponding to failure events are shown in Table 2.3 below. To demonstrate the applicability of the proposed measures, these are compared with the well known existing measures proposed by Gupta and Bhave (1996).

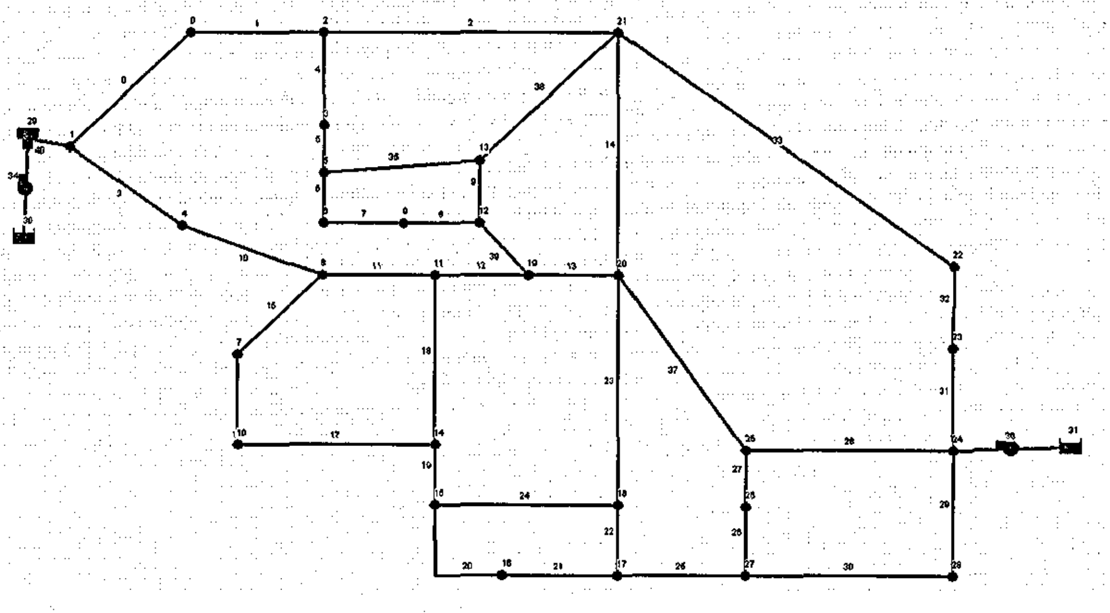


Figure 2.2: Example (30 nodes) network

Table2.3: Performance measures for selected failure events

Pipe	**1**	**3**	**4**	**8**	**9**		**1**	**3**	**4**
Node			**Adequacy**			**DSR_{95}**	**Severity**		**G&B**
1	1.00	0.90	0.96	0.97	0.98	0.80	0.51	0.40	0.96
3	0.91	0.89	0.91	0.93	0.96	0.40	0.50	0.39	0.91
4	0.94	0.94	0.94	0.96	0.96	0.40	0.45	0.34	0.94
5	0.99	0.99	0.92	1.00	1.00	0.80	0.46	0.36	0.92
6	0.95	0.95	0.95	0.97	0.97	1.00	0.70	0.55	0.95
7	0.95	0.95	0.95	0.95	0.97	1.00	0.48	0.36	0.95
8	0.95	0.94	0.90	0.91	0.95	0.40	0.46	0.36	0.90
9	0.98	0.98	0.94	0.94	1.00	0.60	0.89	0.70	0.94
10	0.94	0.94	0.94	0.94	0.95	0.20	0.47	0.41	0.94
11	0.93	0.93	0.87	0.89	0.93	0.00	0.52	0.41	0.87
12	0.96	0.96	0.92	0.93	0.95	0.60	0.46	0.36	0.92
13	0.92	0.91	0.89	0.91	0.94	0.00	0.88	0.88	0.89
14	0.96	0.96	0.94	0.95	0.97	0.00	0.35	0.27	0.94
15	0.92	0.92	0.85	0.87	0.91	0.00	0.35	0.26	0.85
16	0.95	0.95	0.91	0.92	0.95	0.60	0.32	0.23	0.91
17	0.95	0.95	0.92	0.93	0.95	0.60	0.56	0.39	0.92
18	0.95	0.94	0.91	0.92	0.95	0.40	0.41	0.29	0.91
19	0.93	0.93	0.90	0.91	0.93	0.00	0.55	0.42	0.90
20	0.96	0.95	0.93	0.94	0.95	0.60	0.51	0.37	0.93
21	0.92	0.91	0.85	0.87	0.91	0.00	0.44	0.33	0.85
22	0.94	0.94	0.92	0.93	0.95	0.20	0.39	0.29	0.92
24	0.96	0.96	0.94	0.95	0.96	0.80	0.45	0.31	0.94
25	0.95	0.95	0.92	0.93	0.95	0.60	0.48	0.37	0.92
26	0.95	0.94	0.92	0.92	0.95	0.40	0.37	0.28	0.92
27	0.96	0.95	0.94	0.94	0.96	0.60	0.61	0.52	0.94
28	0.96	0.95	0.93	0.94	0.96	0.60	0.38	0.29	0.93
29	0.93	0.93	0.88	0.90	0.93	0.00	0.50	0.39	0.88
30	0.94	0.93	0.90	0.91	0.94	0.00	0.40	0.31	0.90
Equity	0.94	0.97	0.92	0.91	0.91				
NSR_{95}	0.39	0.54	0.89	0.75	0.25				
VRF	0.95	0.94	0.91	0.93	0.95				
NF	0.95	0.94	0.92	0.93	0.95				

Key:

DSR-Demand Satisfaction Ratio

NSR-Node Satisfaction Ratio

VRF-Volume Reliability Factor (Gupta and Bhave, 1994)

NF-Node Factor (Gupta and Bhave, 1994)

G&B-Gupta and Bhave's Reliability Measure

Nodal adequacies indicate the percentage of water shortage experienced by the consumers at nodes for a given failure event. This is the complement of the node reliability factor proposed by Gupta and Bhave (1994). On the other hand volume reliability factor and node factor for a failure event indicates the performance of the entire WDS. In this example both, the nodal adequacies and the node reliability factor suggest that the shortfall in demand is very small at the nodes; majority of the time demand shortfall is less that 10%. For all the failure events both node factor and volume reliability factor are above 0.9 which suggest that the operation of WDS is not critical furthermore these measures provide only an overall indication of the consequences at nodes and the WDS. They neither provide much details of how the nodes experience the failure events nor the failure experience of the consumers. These issues are addressed by the equity, demand satisfaction ratio, node satisfaction ratio and severity.

Equity indicates the distribution of water among the nodes in other words it gives an indication of the distribution of failure consequence among the consumer nodes. This should be considered in conjunction with adequacy of the system. High equity means that distribution of the water among the nodes is highly uniform with respect to their required demand. System adequacy value of 1 and equity of 1 will suggest that the WDS operate satisfactorily, lower values will indicate deterioration in performance. Higher values of adequacy will result in higher equities. But higher equity does not necessarily mean that the system operates with a high adequacy. If for example equity of 0.5 will indicate that the supply among the nodes are the non uniformity in the water supply is high. The higher the equity, the more uniform the supply between the nodes. Therefore, one of the aims in WDS design is have a high equity values during pressure deficient situations.

In the above example the pipe failures 1,3,4,8 &9 result in equities 0.94, 0.97, 0.92, 0.91& 0.91 and adequacies of 0.95, 0.94, 0.92, 0.93 & 0.95 respectively. This suggests the WDS and the nodes operate in a satisfactory manner. That is the maximum demand short fall at nodes is on average 0.08% and the shortfall in demand is almost equally distributed among the nodes as the equities are below 1 and above 0.91.

Node satisfaction ratio is a complementary measure to adequacy and equity, this suggest that the percentage of nodes that satisfies a pre specified demand, in this case 95% of the demand during a failure event. Higher node satisfaction ratio indicates greater percentage of nodes operating above a pre specified percentage of demand. In the above example the node satisfaction ratios for the failure events as shown in the table are 0.39, 0.54, 0.89, 0.75 & 0.25 respectively. These values indicate the percentage of nodes that do not satisfy 95% of the demand during their corresponding failures. If the pre specified demand is lowered to 90% the above values will become 0, 0.04, 0.18, 0.11, 0 respectively indicating only 4%, 18% and 11% percent of the nodes do not satisfy 90% demand during failure of pipe 3, 4 & 8 respectively. Also these values suggest that failures of pipe 1& 9 are much less severe compared to the pipes 3, 4 & 8.

Similarly demand satisfaction ratio suggests the frequency of a particular node satisfying the pre specified demand throughout the whole duration of the failure event. This can also imply the reliability of the node. In this example for the given 5 failure event node 1 has a DSR_{95} is 0.8 that is 80% of the time the node satisfy 95% of the demand. When the pre specified demand is dropped to 90% the DSR_{90} for node 1 becomes 1. That is 100% of the time node 1 satisfy 90% of demand for any failure event.

The severity measure is different from those discussed above as it takes the consumers behaviour and their importance and the consequence into consideration. Therefore, it is capable of determining the failure experience of the consumers. The weight associated with this measure is the important aspect. They help to identify the importance of different consumer groups with respect to their vulnerability to failures.

Severity combines the consequence of the consumers with importance thus indicating the failure experience. According to the weights, it is apparent that higher the severity, the more severe is the consumers' failure experience. For example consider the pipe 1 failure. By analysing the performance of node 3 and 9; it can be seen that the latter node has a smaller flow shortfall than the former one, also the severity of node 9 is (0.89) higher than that of 3(0.39) thus implying that consumers at node 9 will experience a severe failure than that ones at node 3.

In order to compare the performance of the WDS for different failure events, system based measures such as system adequacy, node satisfaction ratios and equity can be employed. In this example criticality of failure decreases in the following order: pipe 9, 1,3,8,4 which is based on system adequacy (percentage of satisfaction of demand) and node satisfaction ratio. A comprehensive analysis of WDS performance is carried out in Chapter 6.

2.8 Conclusion

In this chapter new performance measures are presented for the purpose of evaluating the behaviour and performance of WDS during extreme situations (component failure events and of peak demand periods). This is in light of the fact that existing measures are not sufficient to indicate the important aspects of the WDS during extreme events. Traditionally the performance measures used in the WDS have been developed to evaluate reliabilities and risk of WDS. Reliability and risk measures alone do not necessarily capture the whole performance of the system.

The proposed performance measures, unlike the existing ones, evaluate the distribution of failure consequence through out the system (equity). They also capture the failure experience at nodes by considering the importance of the node and consequence of the failure by way of employing weights. On the other hand, the adequacy, demand satisfaction and node satisfaction ratios present snapshots of different aspects of consequence of failure in WDS.

Some of the measures (equity and adequacy) proposed in this thesis originate from the field of irrigation engineering. The similarities between irrigation systems and WDS enabled those measures to be modified to be applied to WDS.

In order to demonstrate the proposed performance measures, they were applied to an example system (30 node network) and also a case study system. The proposed measures are compared with currently available ones. The results of the example system are provided in this Chapter 2 and that of the case study network is given in Chapter 6.

From the results it was observed that the proposed measures not only give more information about the extreme events but also complement the existing measures. Therefore, it is an improvement in the evolution of performance measures for WDS.

The main criticisms of the proposed and the existing performance measures are that they can only be applied with network analysis models that are sensitive to pressures. The results produced by the measures depend on the type of pressure dependent demand method adopted for network analysis and in the way that extreme events are simulated. In other words the more realistic the simulation of extreme event and the network analysis is, the more accurate the predicted performance of the WDS.

The principal conclusions of this chapter are:

- The performance of the WDS during extreme events cannot be fully understood by using existing reliability, risk and availability measures.
- Appropriate performance measures that are capable of providing additional insight are needed. Hence new measures have been introduced which complement the existing measures.

CHAPTER 3

COMPONENT FAILURE MECHANISM

3.1 Introduction

One of the aims of the water utilities is to provide the customers with an uninterrupted supply and satisfactory levels of service (LOS). However, in reality levels of service to the consumers are often breached as a result of unforeseen events faced by the WDS. The increases in consumer demand due to urbanisation, losses in the distribution system and component failures are the main factors contributing to the unsatisfactory levels of service in WDS. This thesis considers deterioration of WDS only due to component failures.

Pipes, pumps, valves and storage tanks (reservoirs) are the primary components of the WDS. The first three are the ones that often experience failures. The failure frequencies of pumps are very small compared to that of pipes. Malfunction of a pump may be more severe than that of a pipe as the former failure may result in the entire network not getting water. In the mean time, during the latter failure event some or most of the nodes may function within acceptable levels of service.

Failures in WDS are the result of a combined effect of physical, mechanical and operational factors acting on the components. It is not possible to single out their individual contributions. Intensity of a component failure varies with its age. Initially it will have a higher failure rate for a short period followed by a lower and constant failure rate for most part of the life of the component and at the end very high failure rate for the remaining part of its life.

Failure behaviour of components in WDS are of random nature, therefore to simulate the failure behaviour in WDS, a Monte Carlo type technique based on the probability distributions of failure events is employed.

This chapter discusses the behaviour of component failures in WDS and reviews currently available failure prediction and simulation models. It also proposes a method to generate random failure events in the WDS and to simulate the dynamic behaviour of the failure events. The proposed methodology is based on that given by Wagner *et al.*, 1988b, however modifications were incorporated. Furthermore unlike in Wagner's method, the proposed method also generates time to isolate the failure, enabling to simulate the entire failure process of a component.

The proposed methodology is applied to a 30 node network to demonstrate the capabilities and results are provided at the end of this chapter.

3.2 Stresses on WDS

Water distribution systems have certain objectives that need to be met. Those have been discussed in chapter 2. The main issue related to functioning of WDS is how well a WDS can meet these objectives. There are some global pressures that inhibit the system from meeting its objectives. These are classified as:

- Increase in demand.
- Climate change impacts.
- Deterioration of assets.

Unsatisfactory performance of WDS can be attributed to one or a combination of the above mentioned causes.

3.2.1 Increase in Demand

The demand increase in a WDS occurs as a result of social and environmental changes that directly influence the behaviour of consumers and the water supply system (Memon and Butler, 2005). Demand increase forces WDS to breach the desired levels of service provided to the consumers. Figure 3.1 gives an indication of the increase in non irrigable (domestic, industrial and livestock) water use throughout the world.

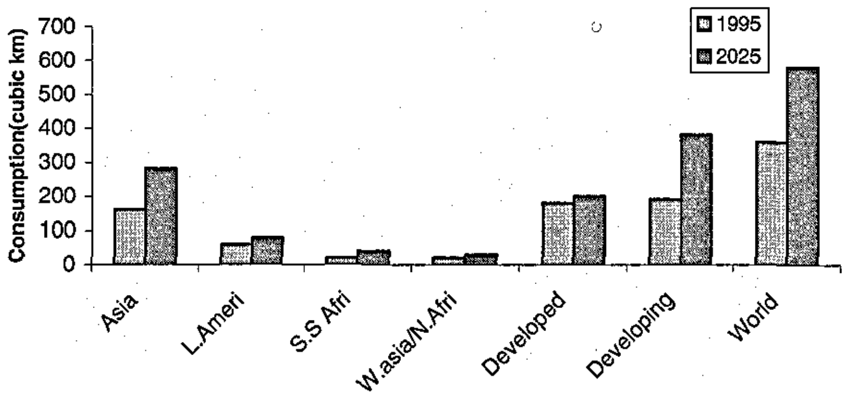


Figure 3.1: Total Non Irrigation Water Consumption by Region (Rosegrant *et al.*, 2002)

Increase in consumer demand without improvements to the WDS assets and increased (water) resources will put severe strain on the system. WDS are designed to accommodate only a certain amount of additional load during its design life. Events such as unexpected increase in populations create a sudden surge in water demand that breach the design values. Such situations prompt the system to operate with reduced levels of service, thus failing to meet the set objectives of the WDS.

Main factors which contribute to the increased demand in a WDS are:

- Urbanisation.
- Improvements in standard of living and life style.
- Population increase.

It is a well known fact that there is a rapid movement of populations from rural areas to urban centres (Vairavamoorthy, 1994). For example between 1950 and 1990 the number of cities with populations of more than 1 million increased from 78 to 290 and this is expected to exceed 600 by 2025 (Yan, 2006). This has put severe strain on the urban infrastructures, especially the WDS making them unable to meet the consumer demand.

Another factor that aggravates the problem of urbanisation and water scarcity is the increase in population. Currently the population increases at an average rate of 1.2% in the world, and in Africa alone the rate is twice the average rate (DFID, Climate change in Africa 2005). This feature is very critical in developing countries. It has been estimated that by 2025, a third of the population in the developing world will face severe water shortages (Seckler *et al.,* 1998).

Rapid urbanisation of cities is a sign of economic development in the region. As a result a cross section of consumers will be achieving higher living standards. This is usually reflected by their lifestyle. Consumers with higher standard of living generally have a higher per capita consumption compared to those experiencing lower standards. This fact is reflected by the difference in per capita consumptions of the developed and the developing countries. A contributing factor towards this phenomenon might be the use of household appliances and other equipment that the latter group does not have the luxury of acquiring them.

The increase in demand caused by the above discussed factors is further aggravated by the depletion of existing water resources. This results due to pollution events and the over exploitation of the sources. The impact of water source depletion on the agriculture may be very significant than on the potable water supply. This is mainly due to that the quantities of water used for agriculture is much higher than that of potable use.

It is well documented in the literature that unplanned urbanisation combined with water scarcity has forced the water supply systems in major cities especially in the developing world to operate intermittently (Vairavamoorthy, 1994; Akinpelu, 2001).

Intermittent systems are where there is supply only a few hours a day with low residual pressures. These systems supply a reduced flow that has negative impacts on the health, hygiene and the quality of life of the consumers. The inconveniences of the consumers are compounded by the unusual timings of the supply in such systems and sometime forcing the consumers to queue for water at times when they would otherwise be rather working (Akinpelu, 2001). Such systems come at a cost to the consumer by way of forcing them to incur capital costs for additional storage facilities.

This situation clearly shows that acceptable levels of service are breached, therefore failing to meet the objectives of providing sufficient quantities of safe drinking water with sufficient residual pressure.

3.2.2 Climate Change Impacts

Some of the unusual and unpredictable environmental changes have been blamed on the climate change phenomenon. Some countries are increasingly experiencing drought conditions, in the mean time others experience devastating floods. These changes in climatic conditions influence the water supply system. Drought conditions in places where there is already a water shortage will further weaken the water supply.

However, there is very little information of the precise impacts of climate change phenomenon on specific locations (DFID, Climate change in Africa, 2005). Most climate change predictions are for long term (2050-2100) and there is great deal of uncertainty in short term predictions and the climate models make predictions on a very broad scale.

3.2.3 Deterioration of Assets

Structural and functional deterioration of water distribution system assets are inevitable. Aging of water distribution assets is a global problem. Some of the water distribution assets serving the utilities in Western Europe and North America are more than 150 years old (Sægrov *et al.*, 1999). It is estimated that 50% of all larger diameter water mains in the 50 largest cities in the US are more than 50 years old (Summers, 2001). Interaction of different factors associated with pipe deterioration makes it a complex process. These factors are mainly categorised into physical (age, diameter, material, length etc.), environmental (soil corrosivity, internal and external loads, location etc.) and operational (break history, leakage record, operational pressure etc.) factors (Yan, 2006). However, the degree of contribution of each of the factors to the deterioration process is unknown.

Deterioration of water pipes has been one of the concerns related to WDS that may pose a public health hazard (Yan, 2006). Aging and deterioration of the water distribution assets compromise the integrity of the water distribution system. This causes water loss from the distribution system through leaks, intrusion of contaminants, loss in carrying capacities of the pipes and also increased failure frequencies. These events will have a direct negative contribution towards the levels of service to consumers, making the system unable to meet the objectives.

Water losses in distribution systems are a common phenomenon, losses occur mainly due to leakage resulting from deteriorated assets, failures and illegal tapping. The water loss in a WDS is categorised mainly into two types: apparent losses and real losses. The first type of losses is due to unauthorised or illegal connections on the system and also due to metering errors. However, the more important component of the water loss in terms water conservation and demand management perspective, is the real loss.

The real losses results from the leakages through joints and cracks in WDS. The high volume of background (undetectable) leakage in the system is due to the large number of joints and fittings on the service connections between the main and the property boundaries (Farley and Trow, 2003). New bursts on the transmission mains and the distribution pipes further aggravate the situation. Most common factors contributing to the real losses are:

- Leakage on transmission and distribution mains.
- Over flow and leakage at storage tanks.
- Leakage on service connection.

It has been noted that WDS losses a considerable amount of water during the distribution process. Water loss in distribution varies country to country based on existing conditions of water distribution infrastructure and water management practices. The losses may range from 44% (Malta) to 2.4 % (Singapore) of the total input, depending on the consumption per service connection (Farley and Trow, 2003). Albeit, there have been speculations about the units used in determining real losses, the amount of water lost as a result of real losses is enormous. OFWAT specified leakage reduction target in 2006 for Thames Water is 860 million litres per day (OFWAT, 2007). Such amount of water if saved will make a big difference in a WDS satisfying the set levels of services to the consumers.

Internal deterioration and aging pipes causes the reduction in the carrying capacities of the pipes, resulting in greater energy losses during the distribution of water. This creates pressure problems in the WDS and also result in inefficient operation of the system. Loss in carrying capacity can be directly related to the bacterial growth in pipe walls. This alters the effective diameter of the pipes. The carrying capacity depends on Hazen Williams's friction coefficient and dimensions of the pipes (Vairavamoorthy, 1994).

Main components in a water distribution system are the pipes, pumps, reservoirs or storage and the valves. These are often susceptible to failure events. Failures are influenced by physical, environmental and operational factors. It is difficult to single out the contributions of individual factors in the failure process. The impact of deterioration on component failure frequencies is a factor of importance. As a result of the deterioration process the structural characteristics of the pipes are compromised. Especially the corrosion pits will affect the pipe wall thickness making the pipes vulnerable to failures.

It is recognised that a pipe which has a history of failures is more likely to fail again than a newer one. This has been acknowledged by Shamir and Howard (1979) and Walski and Pelliccia (1982). They proposed a pipe failure prediction model that determines the break rates at a given time. Their relationship considered the previous break rates and failure frequencies in order to predict the current break rates. Therefore, it is evident that the deterioration of component increases the failure frequencies of the pipes.

In the event of a pipe failure, the WDS will experience a sudden increase in demand due to the loss of water through the burst. The distribution system will operate in a failed mode. Once the burst is found and isolated, the WDS will still operate at a reduced carrying capacity as the failed links are taken out of service. The normal supply will resume only after the repair of the burst is completed. Furthermore, cracks on the pipes may result in ingress of pollutants into the WDS when it is empty. These types of events are more likely to occur in intermittent supplies.

It is imperative to acknowledge that all the above mentioned events (climate change, demand increase and the asset deteriorations) are capable of having a negative influence on the WDS levels of service. This thesis only considers the component failure aspect. Therefore, next section discusses the component failure mechanisms in water distribution systems. The discussion focuses mainly on the pipe failures since they are the events often causing interruptions to the supply.

3.3 Component Failure Mechanism

Components in the WDS are often subject to failures. These events occur at different stages of their life. Remedial action to a component failure event depends on several factors such as the economical life of the component, the available options (to repair or replace) and the availability of resources (financial, technical, and human). Most frequent remedial action to a failure event is repair, as the cost of a repair process is very small compared to the replacement option and also due to the fact that WDS components are repairable. The rest of this section explores the failure behaviour of components particularly considering pipe failures. For a well designed water distribution system, most of the pipes can be considered repairable. The main reasons underlying this nature are:

- The cost of repairs is small compared to replacement.
- The environmental effects due to failure are minimal.
- The availability of additional storage reservoir in the network.
- The redundancies and the diversity associated with the network.

During a pipe failure, a small part of the pipe can be repaired or replaced to restore the pipe to its original state without replacing the entire pipe. The pipe may have undergone several repair events before being replaced. Therefore, successive failures are not identically distributed and also not independent. (O' Conner, 1995). Many repairable systems, including pipes, typically have a "bathtub" shaped failure intensity function (O' Conner, 1995). This is shown in Figure 3.2.

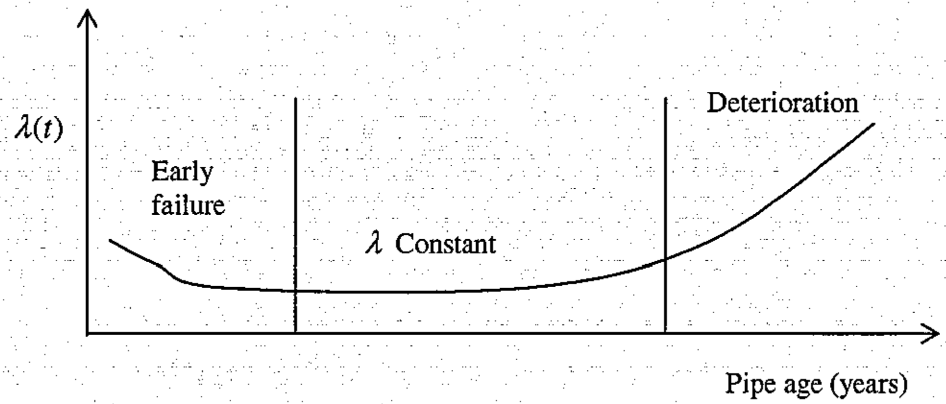


Figure 3.2: Bathtub Curve (O' Conner, 1995)

Where $\lambda(t)$ is the failure rate.

When a pipe is newly installed, the failure intensity can be high and as a result high failure rates. This can be described as a settling in period, possibly due to construction practices. After early faults have settled down, the failure intensity will be smaller and remain relatively constant for long periods of its useful life. Then as the pipe ages, the intensity will begin to increase and the pipes start deteriorating. This is the period of most interest, as eventually the intensity will exceed a certain level, and it will become cost efficient to replace the pipe.

Pipe breaks occur due to excessive external loads, pipe age, internal conditions of the pipe (corrosion pits, cracks), vulnerable joints, stresses due to misalignments, previous pipe break rates, etc. Physical mechanisms of pipe breakages are very complex process often not completely understood. The different indicators that influence the pipe deterioration can be categorised into physical, environmental and operational factors. These are listed in Table 3.1. Several of these indicators are becoming increasingly available from inventory databases (particularly the physical indicators). However, some indicators are difficult to obtain (e.g. the external protection, workmanship, soil condition indicators) due to incomplete data records.

It should be noted that the indicators are not limited to those listed in Table 3.1. These are basic deterioration indicators, past studies indicated that these indicators influence the pipe deterioration most (AWWSC, 2002). This section explains their overall impacts on water pipe deterioration.

Table 3.1 Water pipe deterioration indicator (Yan, 2006)

Physical indicators (1)	Environmental indicators (2)	Operational indicators (3)
Material	Bedding condition	Frequency of supplies
Year of installation	Traffic load	Duration of water supplies
Diameter	Surface permeability	Number of valves
Length	External protection	Number of connections
Joint method	Soil condition	Leakage record
Internal protection	Groundwater table	Complaint frequency
Workmanship	Buried depth	Breakage history

Descriptions of the effects of these factors are given below. This section only provides a summary of the factors that contribute to the pipe deterioration process. A comprehensive review can be found in Yan (2006).

3.3.1 Physical Indicators

3.3.1.1 Pipe material

Water distribution pipes are made of different materials. The rates of pipe deterioration vary from one material to another. This is reflected in the decaying rate of Hazen William friction coefficients (C value) with pipe age. Therefore, the C values of the pipes can be used as surrogate measures to identify the rate of deterioration. Table 3.2 as given in Yan (2006) indicates the variation in C values with pipe age for different materials.

Table 3.2: Typical values of C coefficient for different types of pipe material. (Yan, 2006)

Pipe Material	Age in years								
	New	10	20	30	40	50	60	70	80
DI	140	130	130	120	120	120	110	100	-
PVC	150	140	140	140	140	140	130	-	-
HDPE	140	130	130	130	130	130	120	-	-
AC	150	130	130	120	120	120	100	-	-
PE	130	120	120	120	120	120	110		
PC/RCC	130	120	110	95	70	70	70	-	-
Steel/GI	150	130	130	100	100	100	60	60	60
CI	150	110	100	90	80	70	70	60	-

From the Table 3.2 it can be seen that Steel/GI and pre stressed (PC)/reinforced concrete (RCC) material deteriorate quickly than other materials such as DI, PVC, and HDPE etc.

3.3.1.2. Pipe diameter

Walski and Pelliccia (1982) acknowledged the impact of pipe diameters on the pipe failures. They developed expressions that predict the failure frequencies of pipes, taking the contribution of the pipe diameters into account. Kettler and Goulter (1985) provided a regression equation for the number of breaks versus diameter and time for cast-iron and asbestos-concrete mains in Winnipeg, Canada. Their expressions indicate a strong inverse relationship with pipe failure and diameter. Loganathan *et al.* (2002) indicated that application of Kettler and Goulter's regression equation to pipes in New York, Philadelphia, and Saint Catharines, Canada, also show decreasing failure rates with increasing diameter in these three cities, in which failures were found to increase linearly with time. The reason behind this phenomenon may be that:

- Larger pipes are laid with greater care.
- Pipe wall thickness increases with pipe diameter hence less susceptible to failure .
- Larger pipes are less susceptible to ground movements as they have greater cementing surface area (Cooper *et al.*, 2000).

3.3.1.3 Pipe length

The vulnerability of pipes to failures is directly related to its length. Longer length pipes are much more vulnerable than that of shorter length. This is because longer pipes are more likely to be overstressed resulting in potential longitudinal breaks (e.g. hoop stress – longitudinal breaks caused by transverse stresses). Vulnerability studies of various pipes from earthquake hazards further reinforced that pipe failures increased with pipe length (Yan, 2006).

3.3.1.4 Pipe joint method

Types of joints used in WDS pipes have a significant impact on failure. Joints can be characterised by their strength to withstand stresses, ability of flexibility to withstand movements and water tightness. The joint types vary with pipe material and size. Mays (2000) indicated that welded joints are often used with steel pipes of a diameter of 600 mm and above, while bell and spigot with rubber gaskets or mechanical couplings are common for pipes less than 600 mm. Lead, leadite and rubber joints are often used with cast iron pipes. Most commonly used joint type with ductile iron pipes, asbestos cement pipes, reinforced concrete pipes (RCP) is the rubber joints. This joint allows for some deflection without sacrificing water tightness (Mays, 2000). The rubber gasket joint alleviates the shortcoming associated with leadite and rigid joints in terms of allowance for deflection, while a leadite joint is inferior to a lead joint (AWWSC, 2002).

3.3.1.5 Internal protection

Type of internal protection used in water pipes influences their deterioration process due to corrosion. Internal corrosion can cause pipe degradation (e.g., pitting), which can result in leakage or vulnerability to mechanical failure.

Modern metallic pipes are mostly manufactured with internal linings to prevent internal corrosion from soft or aggressive water. However, older metallic pipes may be unlined and would therefore, be susceptible to internal corrosion. The AWWA Research Foundation has published two manuals that provide a detailed description of internal corrosion processes and their control (AWWARF, 1989; AWWARF/DVGW, 1986).

3.3.2 Environmental Indicators

3.3.2.1 Bedding condition

Formation of voids and loss of support on laid pipes can contribute to pipe failures. Therefore, providing bedding support is an essential part of pipe laying process. Standard pipe installation practices give indications of bedding types needed for different pipe materials and soils. The type of bedding required is determined by a number of factors, including pipe material, size, surface load and working pressure. Bedding type may vary from loose fill to complex bedding consisting of concreted and specially selected back-fill material (Smith *et al.,* 2000). The types of bedding material that pose the greatest threat are silts and sands while those with the lowest degree of impacts are clays.

3.3.2.2 Soil corrosivity

Pipe failures due to external corrosion are primarily caused as a result of the soil corrosivity. The risk of external corrosion of pipes is extremely high in areas with high soil corrosivity than with moderately or non corrosive soils. The corrosivity of the soils is influenced by the soil moisture, supply of oxygen, salts, soil resistivity, and microbial activity (Cunat, 2001). The effect of soil corrosivity on pipes can be negated by taking appropriate measures such as selecting the appropriate pipe material and using cathodic protections. Table 3.3 below gives types of soils and their respective corrosive natures as given in Yan (2006).

Table 3.3: Soil corrosivity for different types of soils (Yan *et al.*, 2006)

Soil type	Corrosivity
Sand	Essentially non-corrosive
Loamy Sand	Mildly corrosive
Sandy Loam	Mildly corrosive
Sandy Clay Loam	Mildly corrosive
Loam	Moderately corrosive
Silt Loam	Corrosive
Silt	Highly corrosive
Clay Loam	Highly corrosive
Silty Clay Loam	Highly corrosive
Sandy Clay	Corrosive
Silty Clay	Extremely corrosive
Clay	Extremely corrosive

3.3.2.3 Workmanship

The human factors in pipe installation are one of the many factors that contribute to the pipe failures. These include not following standard codes of practices due to unavailability or lack of enforcing such methods. This leads to poor workmanship that directly affects the frequency of failures regardless of pipe age and other relevant factors. Workmanship cannot be quantified but is usually indicated using descriptive statements such as bad, good or very good.

3.3.2.4 Surface permeability

Permeability of ground indicates the ability of the ground to allow the movement of moisture. Highly permeable ground surface allows a large amount of moisture to percolate through the ground to the pipe surface. Moisture from the surface carries residual road salts along with it to the pipe surface. This might create conducive environments for corrosion to take place. Therefore, highly permeable soils may act as a factor that contributes to the deterioration process of pipes.

3.3.2.5 Groundwater condition

Ground water in the areas of buried pipe may contribute to the deterioration of pipes due to the quality of water flow. The location of water table may be permanently or intermittently above or below a water pipe. The contributions of ground water to pipe deterioration are from the following ways:

- Water with minerals may corrode pipes. Some groundwater is aggressive towards certain pipe materials.
- Water flowing through the bedding material may cause ground loss and a subsequent lack of support to water pipes.
- Intermittent wetting and drying will make the bedding material unstable.

3.3.2.6 Buried depth

The buried depth has an influence on the structural failure of the pipe. Water distribution pipes must be buried deep enough, in order to avoid damage to pipes by compression due to overhead loads especially traffic loads. Smith *et al.* (2000) suggested that in areas where vehicle traffic is not a concern, the top of water lines should be located at least 15cm beneath the maximum recorded depth of frost penetration, typically 1.2m deep.

Davies *et al.* (2001) reported from observations that pipe defects decreased steadily up to a certain depth and after that the defect rate increases. The first occurrence probably reflects road traffic and the second occurrence reflects the effect of backfill soil and overburden pressure and soil moisture with buried depth.

3.3.2.7 Traffic load

Pipe failure rate increases with traffic load and the traffic load are normally greater on main (principal) roads. However, it should be noted that principle roads are structurally stronger. Therefore, failure due to traffic load on the pipes along principal roads may be minimal. Traffic load therefore, should be considered as a trade-off between the loading and the type of road, rather than being based on a single factor.

3.3.3 Operational Indicators

3.3.3.1 Number of valves

The water distribution systems consist of various types of valves that carry out different functions. Number of valves in the WDS introduces twice as many joints that can create vulnerable points in the distribution system. Furthermore it has been observed that pipes with greater number of valves deteriorate faster than those with less because the operation of valves affects the flow pattern and may also cause pressure waves which increases stresses on pipe wall.

It is therefore, assumed that the pipes installed with valves deteriorate faster than the pipes without valves (Yan, 2006).

3.3.3.2 Frequency of supply

The water supply systems in developing countries usually operated intermittently (Vairavamoorthy, 1994; Akinpelu, 2001). The frequency of water delivery in the pipe may vary (for example from twice a day to once in two days). The intermittent water supply deteriorates the pipes due to the variation of pressure from maximum to zero resulting in the pipes being in a continuous dry and wet situation. Therefore, the greater the intermittency of supply, the greater the deterioration of pipe.

3.3.3.3 Duration of water supply

In intermittent water supply systems, durations of supply vary depending on the availability of water (e.g. 2 hours or 4 hours for each supply). When there is no water in the distribution pipes, they experience wet and dry situations and results in air oxidation of pipe walls. Making the chances of a pipe becoming deteriorated is greater, when there is no water in the pipe.

3.4 Pipe Failure Prediction Models

Pipe failures, as mentioned in the above section are influenced by several factors. The consequence of a failure may be a reduction in the levels of service to consumer. In order to estimate the loss in levels of service, the essential information required is the understanding of frequencies and durations of component failure events. This is achieved by using component failure prediction models.

Pipe failure prediction models can be classified as physical models and statistical models. The physical-based models attempt to predict the pipe failure through estimation of the stress from load (environmental and operational) and the scope and severity of corrosion on pipe walls. Whereas, statistical based models predict the probabilities and/or frequencies of pipe breakage using the past pipe breakage data to project a breakage pattern. These classifications are further subdivided into physical deterministic, physical probabilistic, statistical deterministic and statistical probabilistic models (Kliener and Rajani, 2001; Yan, 2006). A summary of the review of these models is given below. A comprehensive review can be found in Kliener and Rajani (2001) and Yan (2006).

3.4.1 Physical based models

Physical models have been developed in order to try and predict the pipe failures due to the cumulative effect of the physical loads acting on the pipes. Kliener and Rajani (2001) identified the primary components of the complex physical mechanisms that influence the pipe failures as:

- Pipe structural properties, material type, pipe soil interaction and installation quality.
- Internal loads due to operational pressure and external loads due to buried soil, traffic and frost.
- Material deterioration due to the external and internal chemical, biochemical and electro-chemical environment.

The sub division of physical models in to deterministic and probabilistic, distinguishes the applicability of models to different situations based on the availability of data. Deterministic models fail to consider the uncertainties involved with the characteristics of failure event. On the other hand probabilistic models incorporate the uncertainties corresponding to each parameter that contributes to the failure event.

3.4.1.1 Physical deterministic models

One of the main reasons for external deterioration of cast iron and ductile iron pipes is the electro-chemical corrosion. This results in development of corrosion pits on pipe walls which grows with time eventually leading to pipe break. Physical deterministic models estimate the impact of corrosion pits on the residual strength of the pipes.

Doleac *et al.* (1980) proposed models relating the corrosion pit depth and pipe age to the pipe wall thickness of cast iron pipes. The model was validated with 5 pipe samples by comparing the measured pit depth to that of calculated from their model. The comparison produced mixed results and is not sufficient to provide significant validation.

Kiefner and Vieth (1989) developed an analytical model that predict the pressure at which a pipe with a corrosion pit would fail. The model assesses the reduction in structural resistance in the presence of corrosion pits. This model was primarily used with ductile material such as steel pipes that are mainly used in the oil and gas industry. Therefore, the appropriateness of the applicability of this model to cast iron and ductile iron pipes is not clear.

Randall-Smith *et al.* (1992) proposed a linear model to estimate the residual service life of water mains under the assumption that a corrosion pit's depth has a constant growth rate. The model was developed as a rough screening tool to identify potential problems rather than provide a means to predict breaks. Rajani and Makar (2000) developed a methodology to predict the remaining service life of grey cast iron mains by calculating the residual strength of a pipe. The calculation combined the elements of the frost load, axial stress, hoop stress, tensile stress and the remaining wall thickness.

External loads such as the frost, earth and the traffic loads acting on the WDS pipes are one of the main causes of pipe deterioration. These factors have a direct correlation with the pit depths on the pipe walls.

Rajani *et al.* (1996) developed prediction models to estimate the external loads especially the frost loads acting on the buried pipes in trenches and under the roadways. The frost models are complex and some of the input parameters such as the frost heave are not readily available.

Rajani *et al.* (2001) proposed a model based on an experimental study on pit and spun cast iron pipe samples, with and without corrosion pits. The model attempts to establish how the dimensions and geometry of corrosion pits influence the residual strength of grey cast iron mains. The proposed model is based on a small-scale laboratory test and it needs to be validated with large-scale tests. In addition some material properties such as fracture toughness that are used by the model are not readily available for most of pipe material of interest.

Seica and Packer (2004) carried out an extensive test on 111 excavated pipes in Toronto, Canada. The mechanical tests include tension, compression and ring bearing test as well as full-scale longitudinal bending tests. The results confirmed that the mechanical properties of iron exhibit significant variation. It was suggested nothing should be assumed in the attempt to estimate the behaviour and strength of cast iron pipes. Therefore, comprehensive sampling program that includes mechanical testing procedures was needed (Yan, 2006). Seica (2004) also developed a finite element model to estimate the remaining strength of water pipes based on experimentally obtained material properties. Using the tools developed by Randall-Smith *et al.* (1992) and Seica and Packer (2004) and also employing the appropriate corrosion models, the remaining life of a cast iron pipe could be predicted thus the sections which require attention could be identified.

Yan *et al.* (2006) proposed the Pipe Condition Assessment (PCA) model to generate surrogate measures to represent the deterioration of pipes. This model does not predict failure rates, rather it ranks the pipes according to their conditions with respect to deterioration. This model has the ability to incorporate as many factors as necessary to estimate the deterioration of pipes. The PCA proposed by Yan *et al.* (2006) considered the physical, environmental and operational factors in evaluating the conditions of the pipes. This model is different from the other pipe failure prediction models, since it uses fuzzy based techniques. The fuzzy mathematic techniques have been used in order to incorporate factors that cannot be expressed using deterministic quantities such as "surrounding condition (good, bad or excellent), soil corrosivity (high, moderate or mild)" etc.

Once the effects of the factors influencing the pipe deterioration is established using fuzzy compromise programming, (Bardossy and Duckstein, 1992; Yan and Vairavamoorthy, 2003), the pipe deterioration index is developed which represent the degree of deterioration in pipes.

The pipe condition assessment model (Yan *et al.,* 2006), predicts the conditions of the pipe with respect to the deterioration and ranks them from very good condition pipes through to very bad ones. The advantages of Yan *et al.* (2006) model compared to other models are that it considers a variety of factors that influence deterioration of pipes. The main disadvantage of this model when applied to predict pipe breaks is that it only gives a surrogate measure of the condition of the pipe concerned rather than the break rate.

3.4.1.2 Physical probabilistic models

These models estimate the probability of pipe failure by using probability distribution functions of contributing parameters of pipe deterioration.

Ahamed and Melchers (1994) developed a physical probabilistic model to estimate the failure probability of steel pipes based on Spangler-Watkins in-plane pipe-soil interaction model. They used a simple power function to calculate the wall thickness over time. The in-plane tensile stress was related to the age of the pipe by an equation where each parameter and independent variable in the model was then assumed to have a probability distribution with a known mean and variance. The mean and variance of the dependent variable, namely the in-plane tensile stress, was approximated using the second-moment description method. Later, Ahamed and Melchers (1995) included the leakage of fluids through corrosion pits with this model. The leakage rate was modelled as an exponential function of time and the corrosion pitting rate.

Several probabilistic physically-based models have been developed that use the pipe residual strength proposed by Kiefner and Vieth (1989). Hong (1997) suggested a log-normal distribution *for the ratio between observed residual strength of a pipe and the predicted value.* Again Hong (1998) related the probability distribution for the residual strength ratio to the corrosion pit dimensions and developed a probabilistic expression for the load resistance ratio between the operating pressure acting on the pipe and the residual strength of the pipe under pressure. The models proposed are more suited to ductile pipe material since they used the residual strength model proposed by Kiefner and Vieth (1989). The limitations of these models when applying to the water mains are that only the in-plane stresses have been considered and the growth rate of corrosion pits is not explicitly modelled.

The physical mechanisms that lead to pipe breakage are often complex and not completely understood. The physical models developed in the past did not consider all the parameters that influence pipe deterioration. In addition, much of the data required for physical modelling is unavailable or very costly to acquire. Although the physical modelling of pipe breakage may be a robust way to predict pipe breakages, it is limited by existing knowledge and lack of data.

3.4.2 Statistical Models

The statistical models fall into three main categories: deterministic, probabilistic and probabilistic group models (Kleiner and Rajani, 2001). The differences between these models are primarily the consideration of indicators that influence the breakage pattern. The deterministic models calculate the number of breakages using two or three parameter equations and are best applied to homogeneous water mains group. The probabilistic single variate models develop the probability distribution functions of the pipe breakage rate from historical data. The breakage rate is a combined function of many parameters that influence the pipe failure. These parameters may differ from pipe to pipe, and therefore the models are more suited to individual pipes. The probabilistic group derive pipe breakage probabilities by applying probabilistic processes on groups of data. A review of the various methods is presented below.

3.4.2.1 Statistical deterministic models

The statistical deterministic models typically use two or three parameter equations to model the breakage pattern for groups of water pipes that are relatively homogeneous with respect to factors that might influence their breakage pattern. These models are relatively simple to apply but require careful consideration of group partitions schemes. Some of the important studies are reviewed below.

Shamir and Howard (1979) used regression analysis to develop an exponential model for the breakage rate of a pipe as a function of time. The proposed break prediction model that relates pipe breakage to the exponent of its age can be used to find the optimal timing of pipe replacement to minimize the total repair and replacement cost. The proposed relationship is given as:

$$N(t) = N(t_0)e^{A(t-g)} \qquad (3.1)$$

Where t is the elapsed in years, $N(t)$ is the number of breaks per unit length (km) per year, $N(t_0)$ is the number of breaks at the year of installation of pipe, g is the base year time and A is the coefficient of breakage rate growth.

It is assumed that the pipes always have a break rate albeit very small in the beginning of its life (Figure 3.2). Shamir and Howard (1979) did not provide any information on the quality and quantity of the data used in deriving the expression. However, they suggested that regression analysis should be applied to pipes that are homogeneous with respect to the factors that influence the breaks. Shamir and Howard's (1979) two parameter model is relatively easy to implement. The exponential model assumes that all the water mains in a group fail uniformly; this assumption has been questioned in the literature (Kliener and Rajani, 2001).

Walski and Pelliccia (1982) enhanced Shamir and Howard's exponential model by incorporating two additional factors (the ratio of break frequency with previous breaks to overall break frequency for cast iron and the ratio of break frequency for 500 mm diameter to overall break frequency for pit cast pipes) in the analysis to account for the known previous breaks in the pipe and breakage frequency for large-diameter, pit-cast-iron pipes respectively. The first factor implies that once a pipe breaks, it is more likely to break again and the second factor accounts for observed differences in breakage rates in large diameter pit cast iron pipes. The improved model takes the following form:

$$N(t) = C_1 C_2 N(t_0) e^{A(t-g)} \tag{3.2}$$

Where C_1 is the correction factor for pipe break frequency C_2 is the correction factor for pipe size.

Walski and Pelecia's (1982) improved exponential model considered the type of pipe casting, pipe diameter and distinguishes between first and subsequent breaks. They did not indicate how much improvement was made by correction factors on the prediction capability of the model. It is obvious that the factors considered in the model have a direct correlation with the breakage rate of the water mains. It is not very clear, that the assumption of the correction factors to act multiplicatively on the breakage rate, which implies that these factors only have an impact on the initial breakage rate, not on the annual growth of the break rate.

Clark *et al.* (1982) observed a lag between the pipe installation year and the first break and consequently proposed to further enhance the exponential model proposed by Shamir and Howard (1979). They transformed it into a two-phase model comprising a linear equation to predict the time elapsed to the first break and an exponential equation to predict the number of subsequent breaks.

$$NY = x_1 + x_2 D + x_3 P + x_4 I + x_5 RES + x_6 LH + x_7 T \tag{3.3}$$

$$REP = y_1 e^{y_2 t} e^{y_3^T} e^{y_4 PRD} e^{y_5 DEV} SL^{y_6} SH^{y_7} \tag{3.4}$$

Where x_i, y_i are the regression coefficients, NY is the number of years from installation to first repair, D is the diameter of pipe, P is the absolute pressure within the pipe, I is the percentage of overlain by industrial development, RES is the percentage of pipe overlain by residential development, LH is the length of pipe in highly corrosive soil, T is the pipe type (1= metallic, 0=reinforced concrete), REP is the number of repairs, PRD is the pressure differential, t is the age of pipe from first break, DEV is the percentage of pipe length in low and moderately corrosive soil, SL is the surface area of pipe in low corrosive soils, SH is the surface area of pipe in highly corrosive soils.

Clark *et al.* (1982) produced moderate fitness with regression coefficient r^2 values of 0.23 and 0.47 respectively for linear and exponential expressions. The linear equation implies that the covariates act on the time to first break independently and additively. The low value of r^2 suggests that the assumption is not valid and the pipe deterioration is a result of joint action of the factors considered. The exponential model on the other hand considers the breakage rate as an exponential function and is comparable with the other exponential models described above.

Jacobs and Karney (1994) applied a liner regression model to evaluate the breakage rates of water mains. They categorised the pipes into three age groups (0-18, 19-30 and over 30 years) to obtain homogeneous groups.

$$P = a_0 + a_1 L + a_2 A \qquad (3.5)$$

Where, P is the reciprocal of the probability of having a day with no breaks, L is the length of pipe, A is the age of pipe, a_0, a_1, a_2 are the regression coefficients.

The additional data such as the length, age and the breakage histories enable the formation of homogeneous groups. Application of the above model to independent breaks gave better correlation compared to the results obtained from applying the model to all the recorded breaks (Kleiner and Rajani, 2003). The results of the model indicate that independent breaks are more uniformly distributed than the total breaks along the pipes. Generalisation of this phenomenon has been questioned in the literature (Kliener and Rajani, 2001).

In addition to the time exponential models described above, several other time linear models that relate pipe break with age have also been developed. Kettler and Goulter (1985) found a moderate correlation between annual break rate and the pipe age based on a sample of pipes installed within a 10 years period. They suggested a linear relationship between pipe breaks and age. The data in time linear models needs to be divided into homogeneous groups in order to implicitly consider additional factors. McMullen (1982) proposed a time linear model that was applied to the water distribution system of Des Moines, Iowa, USA. They concluded that corrosion was a major factor in water main failure. They observed that 94% of pipe failures occurred in soil with saturated resistivities of less than 2000 Ω cm.

The deterministic models predict breakage rates using two or three parameters based on pipe age and breakage history. In fact there are many factors such as physical, environmental and operational that simultaneously contributes to the pipe breakage. In order for the two and three parameter models to capture a true breakage pattern, the population of water pipes analysed has to be partitioned into groups that are appreciably uniform and homogeneous with respect to factors that influence the breakage. Therefore, the deterministic model implicitly and qualitatively uses the group criteria as covariates in the analysis, which maintains a relatively simple mathematical format.

3.4.2.2 Statistical probabilistic models

The statistical probabilistic models explicitly and quantitatively consider most of the factors contributing to the pipe deterioration. The survival analysis method is the most widely used probabilistic model for water pipe failure. It is a statistical technique that deals with time-to-failure data. The proportional hazards model proposed by Cox (1972) is often used for survival analysis. The proportional hazards model consists of a baseline hazard function and a vector of variates. The model computes the coefficient for each of the variates that indicate the direction and degree of flexing of the survival curve. Cox's proportional hazard model is a general failure prediction model for pipes and is given as:

$$h(t, Z) = h_0(t)e^{b^T Z} \qquad (3.6)$$

Where, t is the time, $h(t, Z)$ is the hazard function (instantaneous rate of failure), $h_0(t)$ is the arbitrary baseline hazard function, Z, b is the vectors of covariates and coefficients (to be estimated by regression) respectively.

The baseline hazard function represents the time dependent aging component whereas, the covariates represent the operational and environmental factors that influence the deterioration of the water main.

Marks *et al.* (1985) proposed to use a proportional hazards model (Cox, 1972) to predict water main breaks by computing the probability of the time duration between consecutive breaks. Multiple regression techniques were used to determine covariates that could affect pipe breakage rates and the baseline hazard function was approximated by a second degree polynomial.

Andreou *et al.* (1987 a&b) and Marks *et al.* (1987) further developed the proportional hazard model to include a two stage pipe failure process. The early stage was observed with fewer breaks and was represented by the proportional hazard model, while the second stage was characterised by frequent breaks and was represented by a Poisson type model. The advantage of their model is that different models were used for different breakage patterns. The two-stage failure model confirmed the observations that only a few pipes failed soon after installation but the time between breaks is shortened after each additional break. The break rate seems to be constant after the third break and this is reflected by the second stage Poisson model.

Constantine and Darroch (1993) modelled the pipe breakage using a Poisson model where the mean breakage is a function of the pipe age.

$$\theta = \theta_0 e^{\alpha Z} \qquad (3.7)$$

$$\lambda = e^{\beta^T z} \qquad (3.8)$$

Where θ, β are the scale and shape parameters respectively, θ_0 is the baseline value, α is the vector of coefficients estimated using regression, Z is the vector of covariates affecting the pipe deterioration.

The resulting cumulative distribution of this model was found to be equivalent to the Weibull cumulative distribution function, hence also known as Weibull process (Kleiner and Rajani, 2001).

Copper *et al.* (2000) developed a trunk mains burst model to estimate the failure risk of water mains greater than 300 mm in diameter. The model was applied to Thames Water's London water supply region where four variables (i.e. number of bursts per hour, pipe diameter, soil corrosivity class and pipe density function) were chosen based on data availability to predict the trunk main failures. A logistic regression model was developed to assess the probability of trunk main failures based on the four key variables. The consequence of the trunk main failure was derived through a floodable area model which identified what area would be impacted by a main failure at postcode level. The risk score of trunk main failure was developed by combining the failure probability and the failure consequence score.

Pelletier *et al.* (2003) developed a model based on survival analysis to predict the annual number of pipe breaks and to estimate the impact of different replacement scenarios. They applied the proposed modelling approach to three case studies. Basic descriptive statistical analysis was carried out in 1996 for the three case study municipalities based on the total pipe length. The statistics showed that breakage rates are high for small diameter pipes. It has been often reported in the literature (Kettler and Goulter, 1985) that small diameter pipes have an increased risk of failure. The statistical analysis for the pipe breakage rate versus the pipes installation period also showed often that it is not the oldest pipes that fail more frequently. This may be caused by other factors such as quality of material and workmanship such as installation techniques. The analysis also showed that the vast majority of pipe breaks occur on pipes made of cast iron, followed by ductile cast iron and PVC. In most municipalities, the record of break repairs is relatively shorter compared to the history of the network, therefore, two different probability distributions have been used for different breakage orders.

The studies reviewed in this section showed that probabilistic models can consider many factors that affect a breakage pattern, therefore homogeneous pipe groups need to be generated. However, historical water mains breakage data for a large number of pipes is needed to derive a probabilistic model.

3.4.2.3 Statistical probabilistic group models

The probabilistic group models derive probability of breakage by applying probabilistic process on grouped pipe-breakage data. These models differ from probabilistic model in that probabilistic models are developed for individual pipes whereas, the probabilistic group models are developed for clusters of pipes.

Goulter and Kazemi (1988) and Goulter *et al.* (1993) developed a model to account for the water mains break-clustering phenomenon based on their observations of the significant temporal and spatial clustering of water main failure in Winnipeg, Canada. They attributed this phenomenon to the damaged bedding condition due to leakage and the repair process that exposed the pipes to low ambient temperature and frost. They defined an initial failure as a clustering domain of a space and a time interval. Any failure occurring within this space and time interval was considered to belong to that cluster and the probability of subsequent breaks in a pipe was predicted with a non-homogeneous Poisson probability distribution. These models provided a significant insight into the spatial and temporal clustering phenomenon of water pipe breakage in Winnipeg, but it is not clear whether it describes a global or a regional clustering phenomenon.

Herz (1996) developed a lifetime probability distribution function based on the principles that had originally been applied to population age classes or cohorts. Herz proposed to apply the model to groups of pipes that are homogeneous with respect to their material type and environmental or operational stress class. This model is capable of modelling the burn in and the wear out phases in the bath tub curve (Kliener and Rajani, 2001). The proposed distributions have the following forms.

$$f(t) = \frac{(a+1)be^{b(t-c)}}{\left[a + e^{b(t-c)}\right]^2} \quad (3.9)$$

$$h(t) = \frac{be^{b(t-c)}}{\left[a + e^{b(t-c)}\right]} \quad (3.10)$$

$$S(t) = \frac{(a+1)}{\left[a + e^{b(t-c)}\right]} \quad (3.11)$$

Where, $f(t), h(t), S(t)$ are the probability density, hazard and survival functions respectively, t is the useful life of pipe, a is the ageing factor (1/year), b is the failure factor (1/year), c is the resistance time (years, pipe will not be replaced at age <c).

The parameters of the model were estimated from historical data. However, the model can only deal with relatively large groups of water mains and not applicable to prioritise individual pipes for rehabilitation (Kleiner and Rajani, 2001).

Deb *et al.* (1998) applied the cohort survival model ("KANEW") to one British and four American water utilities. Herz (1998) presented a case study and a framework to use the cohort model in the long-term planning of water mains renewal. These cohort survival models are useful tools for long term planning of water mains renewal budgets, but the models can only deal with relatively large groups of water mains and is not suitable for individual pipes.

Gustafson and Clancy (1999) modelled the breakage histories of water mains using semi Markov process, where each break order is considered as a "state" in the process and inter break time is considered as the "holding time" between the current and previous states. The main assumption in the semi Markov process is that the time between two breaks is independent, it only depends on the break order. They modelled the breaks in two stages. The time from installation to the first break was modelled by a gamma distribution and the subsequent breaks were modelled using an exponential distribution. Gustafson and Clancy (1999) applied Monte Carlo simulation to predict the break rates. For this purpose they employed parameters derived for the inter failure times.

The model developed by Gustafson and Clancy (1999) predicted inter failure time in the water mains based on historical data. However, this model was found to be inadequate to predict future break rates and they explained that this inadequacy was due to the changing conditions over the years (Kleiner and Rajani, 2001).

The probabilistic group models are based on the observation of the breakage-clustering phenomenon. The clustering of water main breakages is a regional rather than a global phenomenon.

3.4.3 Summary of Failures Prediction Models

The physical models address the failure-causing factors explicitly to assess the condition of the pipe. The data needed to apply these models to estimate the corrosion pit growth of a pipe are difficult to obtain because they pertain to the condition of the pipes laid underground (Loganathan *et al.,* 2002). Statistical models are primarily based on regression and in general have low correlation coefficients to predict failure times. A large number of historical breakage data are needed to establish the model parameters. Furthermore, the effects of many other factors such as environmental (e.g. soil condition and traffic load) and operational indicators (e.g. pressure, leakage) are only treated implicitly.

Both the physical and statistical based models reviewed in this chapter relate to pipe breakage with one or more deterioration factors such as pipe age, material or diameter or use previous breakage data. In deterministic approach, there are many factors that contribute to deterioration and only a few are considered in the development of models. The insufficiency and the inaccuracy of the breakage data makes it difficult to establish the probability distribution function for breakage. The lack of pipe deterioration data (for physical models), the pipe breakage historical data (for statistical models) and the lack of sufficient insight into the complexities of pipe deterioration process are the main difficulties faced in applying these models.

The pipe condition assessment model assesses the condition of pipe by interpreting all the indicators that contribute to the deterioration of a pipe. The model is designed in such a way that it does not need the collection of large amount of data and historical breakage data. The model is based on understanding of different indicators that contribute to pipe deterioration. However, the main shortcoming is that it does not explicitly predict pipe failures.

3.5 Pump Failures Prediction

Pumping stations in WDS are the interface between the water source and the distribution system. They are employed either at extraction points or boosting and supply points. Number of pumping plants in the system is decided by the levels of service (LOS) required and the size of the WDS. Each pumping plant has several pumps arranged either in parallel or in series.

Unlike pipes, pumps are not subjected to stresses due to external physical loads. Failures in pumping stations are mainly from component wear and tare, transient events and tripping due to electrical failures. Frequency of pump failures is stochastic in nature, which can be modelled, based on their failure probabilities.

Arrangement of pumps in a pumping plant is analogous to series and parallel arrangements of electrical circuit systems. The difference between them being that the series arrangement boost the pumping head of the plant whereas, the parallel arrangement is employed to affect the flow through the pumping station. The failure of a pump in a series arrangement makes the whole set of pumps come to a standstill. A failure in the parallel arrangement does not affect the operations of other pumps in the group.

When analysing failures both mechanical and hydraulic failures need to be considered to obtain the realistic effect of the failure on the system. Hydraulic failures are triggered by mechanical failures of the components. Mays (1989) considered hydraulic failures of the pumping units. They proposed expressions for hydraulic availabilities. Duan and Mays (1988) employed a frequency duration model to predict the reliabilities pumping stations. They used this model to estimate the expected number and duration of failures during the period of study. They defined the failure rate (μ), repair rate (η) and frequency (f) in order to generate the failure events which are described below.

$$\mu = \frac{N_f}{t_o} \qquad (3.12)$$

$$\eta = \frac{N_r}{t_r} \qquad (3.13)$$

$$f = \frac{N_f}{t_o + t_r} \qquad (3.14)$$

Where, N_f is the number of failures in a time period, N_r is the number of repairs in a time period, t_o is the total operational time, t_r is the total repair time.

It is usually assumed that the time to failure and time to repair follow an exponential distribution. Failure rate and repair rates are taken to be constants from which failure probabilities of each pumping station is obtained.

3.6. Generating Component Failure Events

Component failure events in WDS are of stochastic nature, which are induced by physical, environmental and operational pressures acting on the components. It is imperative that such events be simulated when assessing the performance of the WDS, so that the random behaviour of the component is taken into account. The failure prediction models discussed above do provide a rational way of predicting component failures. Some of them are not equipped to simulate the random component failure behaviour and also they require extensive amounts of field data.

The failure behaviours of the components are found to follow statistical distributions (Wagner *et al.*, 1988b; Cullinane *et al.*, 1992). Therefore, the random failure events are generated based on corresponding statistical distributions. It is also important to consider the different states of the components in the WDS after failure. The important aspects that influence the behaviour of the WDS due to failure and repair events are their durations. Failure and repair durations depend on factors such as ability of locating the failure event and availability of resources. A detailed discussion on these factors is given in the following section.

3.6.1 Behaviour of WDS during Failure

One of the most important aspects of performance assessment in WDS is to represent the actual behaviour of the components during failures. A component in water distribution system will undergo three different phases; normal mode, failure mode and repair mode. Each of the phases will have their corresponding impacts on the behaviour of the system (Germanopoulos, 1988) which are elaborated below.

- Normal mode: is when the WDS experience no failure events and operates as usual with satisfying the desired levels of services to the consumers. This is the ideal phase.

- Failure mode: is the time between just immediately after the component failure and just before start of the repair.
- Repair mode: is the duration from the start to the completion of the repair process.

During a failure event, the component and the WDS will be in failed mode until the failure has been detected. In the event of pipe failures, WDS will experience a sudden loss of water and reduced pressures. This is usually identified by the loss in the system pressure or information from the public. The duration at which this component remains in the failed mode will be the time between the occurrence of the failure and the isolation of failed component. This depends on the time taken to identify the pipe break and to isolate it.

Isolating the component consists of locating the failed component and isolating it by closing the valves associated with the link. It is very unlikely to isolate only the failed part of the component, instead an entire section may be shut off during the isolation process. Once the failed component is isolated, loss of water from the system is stopped and the pressure in the WDS recovers. However, the system will still operate with a reduced carrying capacity. Repair of the failed component commences immediately after the isolation. The duration of the repair depends on the availability of resources (material, technical and human). The system returns to normal operational mode after the completion of the repair.

The time at which the failure event occurs and the total duration of a failure events are crucial factors in the performance of the WDS. Failure of a hydraulically significant component during peak demand period will result in extremely low pressures in the WDS. On the other hand if the same failure occurs during an off peak time the consequence might not be as significant as that of during the peak time.

3.6.2 Durations of Failure Events

The duration of a failure is the time period from the start of the failure event to the completion of the repair. During this time the network experiences two different scenarios: failure and isolation. During the failure (pipe for example) there will be a free flow of water from the crack on the pipe. The network will start to experience a continuous drop in pressure resulting in reduced levels of service. This dynamic situation lasts until the failed component is isolated from the network. After the isolation the network starts to recover as the water flow is stopped and the levels of service will improve. However, still there will be nodes with inadequate pressure since the network operates at a reduced mode (less hydraulic carrying capacity). This situation will remain until the repair is completed. Therefore, the duration of failure can be broken down into:

- Time to isolation.
- Time to repair.

Time required for an isolation process of a failed component is primarily determined by the time taken to identify, locate, and access the failed component. In the event of a pump failure these three time intervals do not play a significant role as pump failures are easily detected. Location of the pump is known and the time to access depends on the availability of maintenance team. However, for pipe failure events, identifying the failed component is very critical as some times, the failure might be in a remote location (rural area) where it might not be noticeable. Therefore, time taken to isolate the failure might be very long as opposed to a failure event in a populated area where the failure may be easily noticeable.

Times to repair, on the other hand depend on the type of maintenance to be carried out (repair or replacement), availability of equipment and the human resource. Repair time for a failure event at a busy road may be shorter than that of a similar failure event on a road which is less busy. The former one has high priority therefore, the water utility will try to complete the repair as quickly as possible. The data regarding failure times and repair times are not always easily accessible as they are not readily available in water utilities.

3.6.3 Simulating Component Failure

Simulation of random component failure is one of the important parts of performance assessment process in WDS. It has received considerable attention in the literature (Wagner *et al.,* 1988b; Germanopoulos, 1988; Gupta and Bhave, 1996; Tanyimboh *et al.,* 2001; Ostfeld *et al.,* 2002; Tabesh *et al.,* 2004). Majority of the models that represent the component failures do not consider the random behaviour. Those models were limited to isolating selected pipes based on failure probabilities of the components. They also overlooked the different states (failure and isolation) of WDS during the failure event. The WDS performance evaluated by such models do not represent the realistic situations, they rather give an approximate picture of the network for corresponding failure event.

On the other hand random behaviour of component failures were simulated by Wagner *et al.,* 1988b; Ostfeld *et al.,* 2002. They employed a Monte Carlo type technique along with the failure probabilities of components. Pipe and pump failures in the WDS were assumed to follow an exponential distribution (Goulter and Coals, 1986; Shinstine *et al.*, 2001).

Wagner *et al.* (1988b) simulated the random failure behaviour of WDS components for reliability analysis. They used Monte Carlo method to generate failure and repair events of the components. Due to the lack of sufficient field data on failure and repair information of the components, they used probability distributions which reasonably represent the failure and repair behaviour. Following information were assumed in the simulation process by Wagner *et al.* (1988b).

- Pipe failure times follow an exponential distribution.
- Pipe repair durations are uniformly distributed with times from 3-72 hours for all pipes.
- Pump repair durations are log normally distributed with $\mu = 3.93$ and $\sigma = 0.2$.

In the simulation process, a component is identified and its failure events and corresponding repair durations were generated by using appropriate probability distributions throughout the entire simulation period.

Wagner's failure prediction model does consider the failure and repair times but ignores the sudden change of flow in the system due to loss of water resulting from the failure. Component failure is represented by just isolating it from the WDS. They assume that once the component fails, repair immediately follows, this does not represent the realistic situation. Another feature of Wagner's methodology is that all the components were considered one by one when generating failure events.

Ostfeld *et al.* (2002) also employed a Monte Carlo technique to generate component failure, time of failure and the repair duration in order to assess the reliability of WDS incorporating the effects of water quality. Ostfeld *et al.* (2002) did not provide much detail as to how the process was carried out.

3.6.4 Proposed Failure Prediction Method

Majority of the failure prediction models described in the literature do not attempt to simulate the random failure behaviour of the components. More importantly the different phases of the failure events have not been considered. Therefore, it is essential to develop a method that combines the various phases of component failures along with the random component failure behaviour. Wagner's approach to component failure is restricted due to the fact that different failure phases such as dynamic behaviour of failure (immediately after failure), repair event were not considered instead they only isolated the component ignoring the dynamic event. Wagner's method simulated the random behaviour based on "the pipe mean time to failure". The repair durations of the component were obtained again using Monte Carlo method. Typical steps in a Monte Carlo method to generate failure times are shown in Figure 3.3 below.

```
Given: Component failure time distributions Pr_i
Given: Number of components n
Number of iterations N_iter
Start
Do j = 1
{
        Do i = 1
        {
        Randomly generate failure times T_i for each component
                {
                Evaluate failure times for all iterations
                }
        } While i ≤ N_iter
                Evaluate ensemble mean of failure times
} While j ≤ n
Component status report
End
```

Figure 3.3: Steps in Monte Carlo method

A component failure model must be capable of simulating the random component failures and represent the different states in the WDS. Wagner's approach covers the first part of the model, but to represent the two distinct states during failure, method proposed by Germanopoulos (1988) is used.

Germanopoulos (1988) employed a pipe arrangement to simulate the dynamic failure situation of the pipes. However, he did not attempt to simulate the random failure behaviour of the components. Therefore, this section attempts to combine both Germanopoulos' and Wagner's approaches to have a method that is capable of predicting the random failure behaviour of components as well as to simulate the different phases of failure.

A detail of the simulation of different phases of component failure behaviour as given in Germanopolous (1988) is presented in Chapter 6. This section only explains the methodology involved in obtaining the random component failure times, times to isolation and repair times.

For pipe failure simulations, inter failure times of the components are obtained from field records. In the event of lack of field records, approximate inter failure times were obtained from the empirical relationships given in the literature (Cullinane *et al.*, 1992; Walski and Pelliccia, 1982). The pipe inter failure times are assumed to be exponentially distributed and repair times are assumed to be uniformly distributed with 3-72 hours as given in Wagner *et al.* (1988b). Between the pipe failure and repair events the failed pipe must be isolated from the system. The time to isolate the failure event depends on how quickly the location of the failed component is identified. The time taken to isolate the failure event varies depending on the location of the failure. Due to the lack of "time to isolation" data, in this section the time to isolation is assumed to be 50% of the repair time. This assumption helps to demonstrate the effects on the WDS during the failure (dynamic situation) mode of the components. It should be noted that in this section, it is not intended to demonstrate the sensitivities of the times to isolation on the reliability of the WDS.

Walski and Pelliccia (1982) proposed an empirical relationship to evaluate the mean time between failures of pipes in the event of lack of field data. The relationship is given as:

$$MTBF = 0.001873D^{1.462131} \qquad (3.18)$$

Where, $MTBF$ is the mean time between failures (days), D is the pipe diameter in millimetres.

The above information on component failures was used to generate component failure times, times to isolate the component from failure state and repair times. Monte Carlo approach presented in Figures 3.3 and 3.4 below was employed in the determination of random failure events. The procedure was coded using Matlab. The main advantage of the method proposed in this section is that it incorporates the methods proposed by Wagner *et al.*, (1998b) and Germanopolous (1988). These two methods combined produces a method that can both simulate the random failure behaviour (as in Wagner's method) and the different phases of the failure event (as in Germanopolous' method).

In this thesis component failures generated were restricted for duration of 10 years. This was to reduce the number of simulations. This restriction was acceptable as this thesis only attempts to demonstrate the methodology adopted in predicting component failures. However, in reality the total simulation period of operation need to be taken for the simulation.

Once the component failure times, isolation times and repair times are generated, they need to be simulated with the network analysis program. Steps involved in this process are shown in chapter 6.

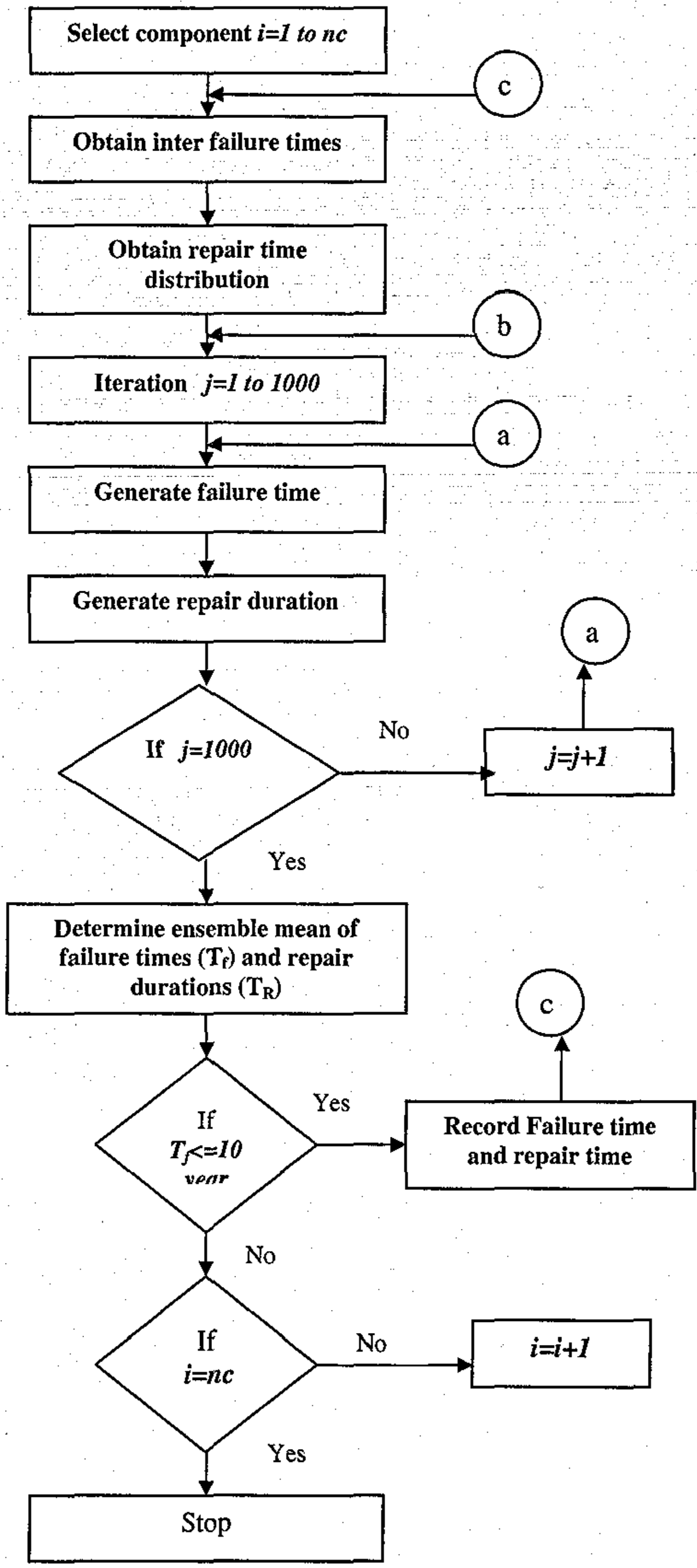


Figure 3.4: Generating Component Failure Events

3.7 Example Application

To demonstrate the simulation method described in this thesis, an example application is presented for the 30 node network given in chapter 2. The mean times between failures of the network are given in Table 3.4 below based on the method described above in this chapter. Also the random failure events generated using Monte Carlo method is shown in Table 3.5. The simulation was carried out for a period of 10 years. In table 3.5 the notations FT and RD, represent "failure time and "repair duration" respectively.

Table 3.4 Pipe inter failure times

Pipe ID	Diameter (mm)	Length (km)	Inter Failure Time(Years)	Pipe ID	Diameter (mm)	Length (km)	Inter Failure Time(Years)
1	300	0.30	3.70	20	250	0.25	9.58
2	300	0.30	4.03	21	300	0.30	10.78
3	300	0.30	2.08	22	300	0.30	11.79
4	300	0.30	1.72	23	300	0.30	3.81
5	300	0.30	4.68	24	300	0.30	2.74
6	250	0.25	10.48	25	300	0.30	2.37
7	250	0.25	11.70	26	150	0.15	8.33
8	250	0.25	8.05	27	300	0.30	2.38
9	150	0.15	8.33	28	150	0.15	2.98
10	150	0.15	3.93	29	150	0.15	3.93
11	250	0.25	6.35	30	200	0.20	2.53
12	300	0.30	5.10	31	300	0.30	2.15
13	200	0.20	4.31	32	300	0.30	10.78
14	200	0.20	4.30	33	300	0.30	11.79
15	200	0.20	8.62	34	300	0.30	14.71
16	300	0.30	2.57	35	150	0.15	2.60
17	150	0.15	5.24	36	300	0.30	8.33
18	300	0.30	11.79	37	150	0.15	14.71
19	150	0.15	2.80	38	200	0.20	2.53

Table 3.5 shows the results of the 38 pipes the example 30 node network. The results indicated that a single pipe has a maximum of 4 failures in 10 year duration. Also the pipe failure times obtained from the simulation suggests that there are no simultaneous failure events among the pipes. This is consistent with the Gupta and Bhave, (1996) assumption that simultaneous failure events in WDS are negligible.

Table 3.5: Pipe failure and repair times

Pipe No	Failure1		Failure2		Failure3		Failure4	
	FT(days)	RD(hours)	FT(days)	RD(hours)	FT(days)	RD(hours)	FT(days)	RD(hours)
1	735	27	0	0	0	0	0	0
2	2117	50	3175.9	19	0	0	0	0
3	412.8	28	1277.5	9	2299.5	36	0	0
4	1533.6	45	3139.4	15	0	0	0	0
5	1642.7	52	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0
10	3394.1	17	0	0	0	0	0	0
11	2226.5	6	3540.7	27	0	0	0	0
12			0	0	0	0	0	0
13	3759.5	8	0	0	0	0	0	0
14	2646.2	11	0	0	0	0	0	0
15			0	0	0	0	0	0
16	453.7	15	839.3	5	2372.5	22	0	0
17	3796.4	20	0	0	0	0	0	0
18			0	0	0	0	0	0
19	2993.7	45	0	0	0	0	0	0
20	2409	30	0	0	0	0	0	0
21	0		0	0	0	0	0	0
22	0		0	0	0	0	0	0
23	2664.7	60	3358	27	0	0	0	0
24	1204.5	5	1715.5	56	2409	13	0	0
25	1496.5	18	0	0	0	0	0	0
26			0	0	0	0	0	0
27	1825.4	7	3285	9	0	0	0	0
28	2920	68	3540.4	39	0	0	0	0
29	949	40	2007.3	21	3505	71	0	0
30	2555	42	0	0	0	0	0	0
31	1679	51	0	0	0	0	0	0
32	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0
34	0	0	0	0	0	0	0	0
35	512	26	0	0	0	0	0	0
36	2190	7	0	0	0	0	0	0
37	1460	55	3433	70	0	0	0	0
38	1095	74	0	0	0	0	0	0

The failure times generated for the pipes vary from 454 days to 3797 days therefore, the failure events are spread throughout the 10 year period. Majority of the failure events occur after 1000 days (or 3 years). This characteristics is consistent with the bath tub curve (Figure 3.2), as initially components experience a few failures (early failures) followed by constant failure rate (settling in period) and then components go into the deterioration phase as failure rate increases towards the 10^{th} year.

3.8 Conclusion

This chapter discusses the methods of modelling failure behaviour of WDS components, especially pipe failures. Failures in WDS are unpredictable events, the most vulnerable components of the WDS are the pipes. General behaviour of the components with age can be represented by the "Bath tub curve". The life of a component is described in three phases namely settling in period (early failures), useful life and deterioration.

Existing failure prediction models describe different phases of the bath tub curve. These models are categorised into physical, statistical and pipe condition assessment models. The physical models associate the failure-causing factors to the condition of the pipe. The data required for these models are difficult to obtain because they pertain to the condition of the pipes laid underground. Statistical models are based on regression analysis. A large number of historical breakage data are needed to establish the model parameters. Furthermore, the effects of many other factors such as environmental and operational indicators are only treated implicitly. The pipe condition assessment models require information on the characteristic of the pipes and contributing factors to the deterioration process. Unlike the physical and statistical models, pipe condition assessment models only evaluate the condition of pipe in qualitative terms (such as good, very good bad etc.). The main disadvantage of the above mentioned failure prediction models is that they do not represent the random behaviour of the pipe failure and also do not give any indication of failure times.

This chapter uses the Monte Carlo method to simulate the pipe failures in the WDS. The failures are based on inter failure times that are assumed to follow an exponential distribution. The repair times of each failure is simultaneously generated with failure events assuming the repair times are uniformly distributed as given by Wagner. Results of the failure prediction model applied to the example network are given in this chapter and it can be seen that simultaneous failure of components is very rare and in this case none.

The failure events that are randomly generated by the failure prediction model are transferred to the network analysis model where they are simulated using the arrangement proposed by Germanopoulos (1988).

The main criticism of this method is the assumptions and parameters used for failure time distributions. These assumptions were obtained from Wagner *et al.* (1988b). The application of these assumptions does not hinder the process of the performance assessment discussed in this thesis mainly due to the fact that the assumptions have been accepted as reasonable Wagner *et al.* (1988b) and this chapter only tries to identify a method that is capable of simulating random failure events in WDS.

The principal conclusions of this chapter are:

- There is still a lack of sufficient insight into the complexities of pipe deterioration process.
- Existing pipe failure prediction models demand extensive data and in some instances they are difficult to obtain (buried pipes).
- A failure prediction model based on Monte Carlo method is used in this chapter to demonstrate the random behaviour of the pipe failures in WDS.

CHAPTER 4

PRESSURE DEPENDENT DEMAND IN WATER DISTRIBUTION SYSTEMS

4.1 Introduction

Water distribution systems (WDS) are important lifeline infrastructure systems. In order to have a better understanding of these systems mathematical modelling is essential. Initially analysis of WDS was carried out manually by solving network continuity and head loss equations. Development of efficient algorithms and advances in computing prompted the automation of water distribution network analysis.

Water distribution network analysis is primarily carried out to assess how networks respond to consumer behaviour. Apart from this, network analysis is also used in evaluating optimal strategies for rehabilitation and repair of water distribution components. Improvements in infrastructure management have resulted in network analysis being incorporated with optimisation techniques, especially to obtain optimal designs of WDS and to devise pipe replacement and rehabilitation options. One of the most important applications of network analysis methods is in the assessment of the performance of WDS during extreme events, especially during component failure and peak demand conditions.

It is important to note that the common network analysis formulation uses a demand driven approach. In this instance the main assumption is that nodal demands are met irrespective of system pressure. This approach does not give reasonable predictions when applied to deficient networks with failure events. Therefore, alternative pressure dependent demand methods need to be applied.

The commonly adopted pressure dependent demand approach incorporates pressure dependent demand (PDD) functions with network analysis. Several different PDD functions have been proposed for this purpose and each of them has its individual strengths and weaknesses. In this chapter an alternative method to analyse deficient networks based on micro level modelling of WDS is proposed. Motivation for this approach is from the application of secondary networks for lumping secondary nodes (households) in intermittent supplies.

This chapter begins with a brief description firstly of the demand driven analysis method followed by the pressure dependent demand analysis. A comprehensive review of existing pressure dependent demand methods and functions has also been provided. Shortcomings of conventional demand driven and pressure dependent methods are highlighted. Finally, proposed method of micro level modelling is presented with an application.

4.2 Demand Driven Analysis Method

The demand driven formulation has been the norm for analysing water distribution networks operating under normal conditions. This formulation is not sensitive to demand variations in the system, in other words, the nodal demands are assumed to be satisfied regardless of the system pressure. Therefore, a demand node in the network will receive the required amount of water irrespective of the nodal pressure. This approach gives reasonable results for water distribution systems operating under normal operating conditions (Tanyimboh and Tabesh, 1997). However, when subjected to extreme situations the demand driven method deviates from being representative of actual conditions of the network. This is as a result of not considering the influence of the pressure variation on nodal discharge. A brief description of the demand driven network analysis process is given below.

4.2.1 Formulation of Network Analysis Problem

The flow in a WDS is governed by the nodal flow continuity equation and loop head loss equation. These two equations depict conservation of mass and energy.

The nodal flow continuity equation states that the algebraic sum of flows at node is zero.

$$\sum_{j\in J_i} Q_{ij} + C_i = 0; \quad \forall i \in NPN \qquad (4.1)$$

Where Q_{ij} is the flow in the network element connecting nodes i and j; C_i is the consumption at node i; J_i are all nodes connected to node i and NPN is the number of pressure nodes.

The loop head loss equation states that the algebraic sum of all head losses around any closed loop in the network is zero.

$$\sum_{\forall i,j\in L_l}\delta_{ij}^{l}\Delta h_{ij}=0 \quad \forall l\in NL \qquad (4.2)$$

Where the summation is taken over all elements in the loop L_i; Δh_{ij} is the head loss across the element between nodes i and j; δ_{ij}^{l} is given by: δ_{ij}^{l} is +1,-1 or 0 depending on whether the flow is on the same direction as the loop L_i, the opposite direction or otherwise respectively.

The next part of the analysis is to select the state variables of WDS and formulate the above equations in terms of these variables. In this section nodal formulation is employed as it reduces the dimensionality of the problem. The state variables in the nodal formulation are the unknown nodal heads. In this case, there are as many equations as the number of unknowns, which is equal to the number of pressure nodes in the network.

Flow through the network elements can be expressed in terms of nodal heads at the ends of an element using head flow equations. Head flow relationships of different network elements of the WDS are given in Vairavamoorthy (1994) and Akinpelu (2001). Using these equations, the nodal flow continuity equation is given by:

$$\sum_{j\in J_i}\phi_{ij}(H_i,H_j)+C_i=0; \quad \forall i\in NPN \qquad (4.3)$$

Where ϕ_{ij} is the head flow relationship for the network element between nodes i and j; H_i, H_j are heads at node i and j respectively; C_i is the consumption at node i; J_i are all nodes connected to node i and NPN is the number of pressure nodes.

4.2.2 Network Simulation Algorithm

The water distribution network elements have non linear head flow relationships. Therefore, their behaviour is represented by a system of simultaneous non linear equations. Solution of these set of non linear equations is obtained by applying an iterative numerical process. In this section, application and the solution methods of the Newton-Raphson Method (NRM) is briefly described. Comprehensive descriptions of different numerical solution methods (NRM, linear theory, gradient method) for network analysis can be found in standard text books and also in Reddy (1990), Vairavamoorthy (1994) and Akinpelu (2001). In this thesis nodal formulation is considered in illustrating the network analysis for the reasons mentioned above.

The nodal formulation in terms of unknown nodal head H for a network with N pressure nodes $(N = NPN)$ is given by equation 4.4.

$$\begin{aligned} &f_1(H_1, H_2, ..., H_N) = 0 \\ &f_2(H_1, H_2, ..., H_N) = 0 \\ &\quad\cdot \\ &\quad\cdot \\ &\quad\cdot \\ &f_N(H_1, H_2, ..., H_N) = 0 \end{aligned} \qquad (4.4)$$

This can be represented in vector form as:

$$f_i(\underline{H}) = 0 \,; \forall i \in N \qquad (4.5)$$

In this process, the objective is to obtain a solution vector $\underline{H}^*$ that satisfies equation (4.5). The algorithm starts with an initial approximation vector $\underline{H}^k$ which is close to the solution vector $\underline{H}^*$. When applying the NRM, a linear set of equations is solved to obtain a correction vector $\delta\underline{H}^k$. This assists in evaluating an improved approximation of $\underline{H}^{k+1}$ which is given by:

$$\underline{H}^{k+1} = \underline{H}^k + \delta\underline{H}^k \qquad (4.6)$$

Where $\delta\underline{H}^k$ is determined using the following linear equations:

$$\nabla f_i(\underline{H}^k)^T \delta H^k = -f_i(\underline{H}^k); \;\; \forall i \in N \qquad (4.7)$$

This can be represented in matrix notation as shown below:

$$\begin{bmatrix} \dfrac{\partial f_1}{\partial H_1} & \cdot & \cdot & \dfrac{\partial f_1}{\partial H_N} \\ \cdot & & & \cdot \\ \cdot & & & \cdot \\ \dfrac{\partial f_N}{\partial H_1} & \cdot & \cdot & \dfrac{\partial f_N}{\partial H_N} \end{bmatrix} \cdot \begin{bmatrix} \delta H_1^k \\ \cdot \\ \cdot \\ \delta H_N^k \end{bmatrix} = - \begin{bmatrix} f_1(H^k) \\ \cdot \\ \cdot \\ f_N(H^k) \end{bmatrix} \qquad (4.8)$$

The matrix of the first derivatives of $f_i(\underline{H})$ is called the Jacobean matrix.

This iterative procedure is terminated when;

$$\left\| \delta H^k \right\| < \varepsilon \qquad (4.9)$$

Where $\| \;\|$ is the Euclidean norm, and ε is a specified tolerance.

The heads at the node when the Euclidean norm falls below the specified error are the actual heads at the nodes. Once the heads are established, flows are derived from the head-flow relationships.

This is a steady state analysis of the WDS. However, this analysis can be extended to simulate the changes in the network over time by accounting for the variations of the network boundary conditions and combining each steady state solution. This is generally called the extended period (EPS) analysis. Details of performing an extended period analysis are given in the next section 4.2.2.1.

4.2.2.1 Extended period analysis methodology

The EPS methodology basically evaluates the boundary conditions of the network (reservoir levels) using the predictor corrector method. The new boundary condition is used to obtain the nodal heads and outflows. Steps in the predictor corrector method employed in the EPS are given below.

As mentioned above the two steps in the extended period simulations are:

- Static solution for the network at time T .
- Reservoir levels projected for time $T + \Delta T$ based on the results of the static solution.

The method of estimating the reservoir levels for the time $T + \Delta T$ is explained below:

Predictor:

1. Reservoir levels at the beginning of the static simulation is $H(T)$ and from the results of the static solution, net inflow into the reservoir is $Q(t)$.
2. Reservoir level $H^*(T + \Delta T)$ is approximated to

$$H^*(T + \Delta T) = H(T) + \left[\frac{dH}{dT} \right]_T .\Delta T \qquad (4.10)$$

Where $\left[\frac{dH}{dT}\right]_T = [CA]^{-1}.Q(T)$ and CA is the cross sectional area of the reservoir

3. The Static solution for the network at $T+\Delta T$ is carried out with reservoir level equal to $H^*(T+\Delta T)$ and $\left[\frac{dH}{dT}\right]_{T+\Delta T}$ is obtained as above.
4. Corrected value of the reservoir head is found at time $T+\Delta T$

$$H(T+\Delta T) = H(T) + \frac{\Delta T}{2}\left\{\left[\frac{dH}{dT}\right]_T + \left[\frac{dH}{dT}\right]_{T+\Delta T}\right\} \qquad (4.11)$$

5. If $\left|H(T+\Delta T) - H^*(T+\Delta T)\right|$ is less than the specified tolerance then $H(T+\Delta T)$ is taken as the reservoir level at the next time step. Heads and flows for the next time step are obtained.
6. If $\left|H(T+\Delta T) - H^*(T+\Delta T)\right|$ is greater than the specified tolerance then $H^*(T+\Delta T) = H(T+\Delta T)$ and continue process from step 3.

This research is concerned with the performance assessment of water distribution systems during extreme events. In such situations WDS will experience pressure deficiencies. The assumptions of demand driven analysis are no longer applicable when the system becomes pressure dependent, hence alternative analysis approaches need to be adopted.

Pressure dependent demand approach is the common method employed to analyse pressure deficient systems. Current pressure dependent demand approaches use pressure dependent demand (PDD) functions. In general PDD functions in network analysis are used either to simulate intermittent systems or to simulate failure scenarios in water distribution systems.

4.3 PDD Analysis Method

Analysing pressure dependent systems is not as straight forward as conventional demand driven methods. Generally when analysing the water distribution network using the PDD method, the PDD relationship is integrated with the network analysis program (Germanopolous, 1988; Reddy, 1990; Vairavamoorthy, 1994 and Akinpelu, 2001). In a few of the PDD approaches the pressure dependent demand relationship is not directly incorporated with the network analysis (Wagner *et al.*, 1988b; Fugiwara and Ganesharaja, 1993; and Tanyimboh *et a.*, 2001). However, pressure dependent nodal outflows are determined retrospectively. These methods have been criticised in the literature on the basis that they do not account for the flow redistributions in the network.

The difference between the conventional demand driven and the pressure dependent analysis is the incorporation of pressure a dependent function into the node flow continuity equation, as shown below.

$$\sum_{j \in J_i} \phi_{ij}(\underline{H}_i, \underline{H}_j) + \Phi_i(\underline{H}_i - \underline{e}_i) = 0; \quad \forall i \in NPN \qquad (4.12)$$

Where $\Phi_i(\underline{H}_i - \underline{e}_i)$ is the pressure dependent demand function corresponding to node i; $\underline{H}_i, \underline{e}_i$ are the head and elevation at node i.

The primary difference between equations 4.3 and 4.12 is that in the latter equation consumer demand is variable depending on the pressure at the node. Therefore, when solving the system of equations with the pressure dependent demand functions, an additional term is added into the Jacobean matrix. In other, words the diagonal terms of the Jacobean matrix given in equation 4.8 will have an additional term from the pressure dependent demand function which are given below.

$$\frac{\partial f_i}{\partial H_i} = \frac{\partial(\phi_{ij}(\underline{H}_i, \underline{H}_j) + \Phi_i(\underline{H}_i - \underline{e}_i))}{\partial H_i} \qquad (4.13a)$$

$$\frac{\partial f_i}{\partial H_j} = \frac{\partial(\phi_{ij}(\underline{H}_i, \underline{H}_j))}{\partial H_j} \qquad (4.13b)$$

The remaining steps in solving the set of node flow continuity equations follow on from that of the demand driven method.

4.4 Pressure Dependent Demand Functions

This section reviews different PDD functions in water distribution network analysis. Existing PDD functions can be categorised into two. The first type is only suitable for systems in developed countries where fully pressurised continuous supplies exist. These functions usually specify a minimum and desired head at nodes within which the pressure dependent demand behaviour is displayed by the function. When the head goes beyond the desired head the PDD function predicts a constant demand. The node starts to receive water only when the nodal head reaches the minimum head. This behaviour of the PDD function is in line with the consumer behaviour of fully pressurised continuous systems.

The second type of PDD function is applied to intermittent systems where consumer outlets behave like orifices (uncontrolled). Consumers in an intermittent supply tend to keep outlets open throughout the supply period (Vairavamoorthy, 1994 and Akinpelu, 2001). Therefore, the PDD function does not show a constant flow for nodal heads beyond the required or desired heads. Typical PDD flow characteristics of continuous and intermittent systems are shown in Figures 4.1 a and 4.1 b respectively.

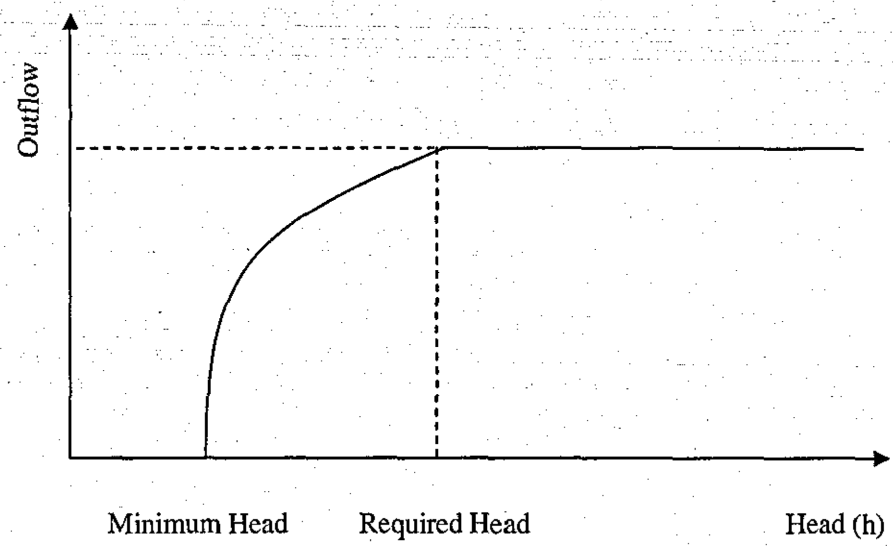


Figure 4.1a: PDD function for continuous systems

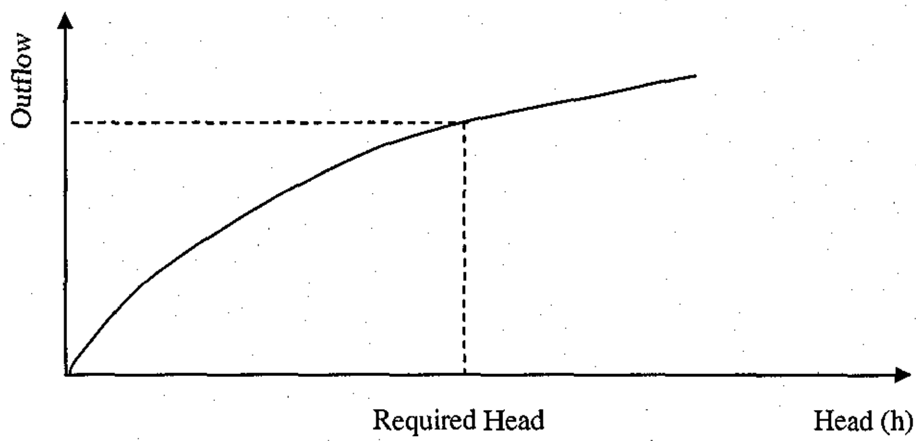


Figure 4.1b: PDD function for intermittent systems

In the literature a number of PDD functions have been proposed (Germanopoulos, 1988; Wagner *et al.,* 1988b; Vairavamoorthy, 1994; Tabesh *et al.,* 2004). These functions have short comings and advantages, but so far there have been no indications given in the literature as to how to identify the most accurate PDD function for the analysis of WDS. In this section the PDD functions are investigated based on their applicability to continuous and intermittent systems.

4.4.1 PDD Functions for Continuous Systems

Germanopoulous (1988) proposed an empirical negative exponential relationship for pressure dependent analysis of extreme events in continuous systems. The PDD relationship is given below.

$$q_i = q_i^*(1 - \alpha e^{-\beta h_i / h_i^*}) \qquad (4.14)$$

Where q_i^* is the nominal consumer demand at the node, α_i, β_i, h_i^* are constants for a particular node, h_i, q_i are nodal pressure and flow respectively.

Figure 4.2 illustrates characteristics of Germanopoulos' PDD function. When the available pressure exceeds the required pressure, demand is no longer sensitive to pressure: a realistic scenario in continuous systems. However, this function does not explicitly relate to the minimum required head. The applicability of the function to WDS very much depends on the coefficients α_i, β_i, which are supposed to reflect the secondary network characteristics. Germanopoulos (1988) did not provide clear indications on how to determine the coefficients of the function and therefore, they are difficult to determine; furthermore they are node specific. These shortcomings associated with the function raise questions on its applicability.

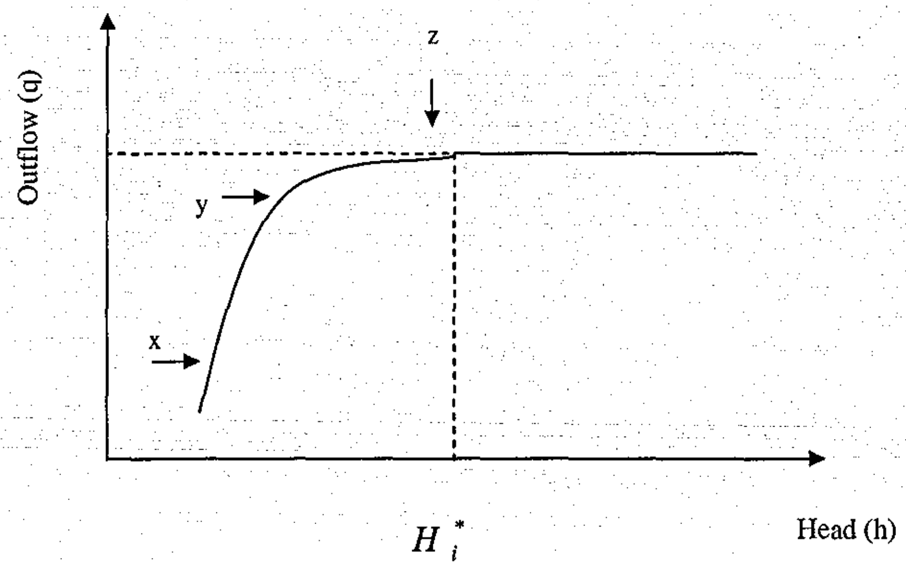


Figure 4.2: Germanopoulos' PDD function

A key observation of Germanopoulos' PDD function is that between points "x" and "y" for a small change of head there is a larger flow variation, whereas between points "y" and "z" for a larger head variation, corresponding flow variation is small. Figure 4.3 shows the PDD relationships for different values of α_i, β_i.

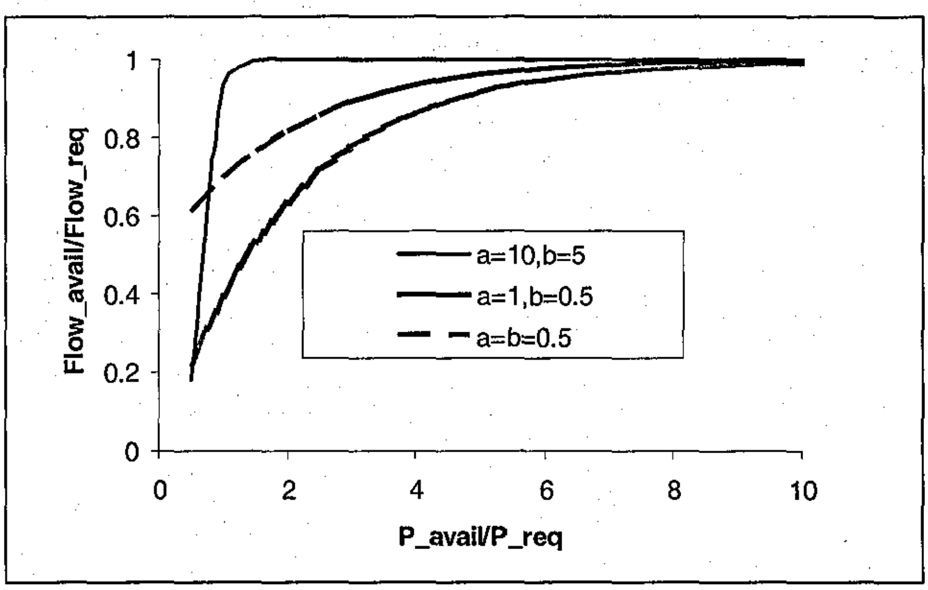


Figure 4.3: Germanopoulos' PDD function

Germanopoulos (1988) used the function with coefficients $\alpha_i = 10, \beta_i = 5$ respectively as shown in Figure 4.3. It is also clear from Figure 4.3 that coefficients of the PDD function depend on the desired head at the nodes as desired heads vary for different values of the coefficients. Also, lower values of the coefficients produces lower nodal outflows even for higher values of head. This was also observed by Gupta and Bhave (1996).

Gupta and Bhave (1996) modified Germanopoulos' function such that it only consisted of one coefficient instead of two and they also introduced a minimum head into the function. The modified relationship is of the form:

$$q = q_i^*(1 - 10^{-c_i[(h_i - h_i^{\min})/(h^* - h_i^{\min}]}) \qquad (4.15)$$

Where $h_i^{\min}$ is the minimum required pressure at node i, h^* is the desired pressure at node i.

Both equations 4.14 and 4.15 have exponential relationships, however the inclusion of the minimum pressure to equation 4.15 tends to improve its general applicability. Germanopoulos' PDD function has been used by Jowit and Xu (1993) and Gupta and Bhave (1996), however they did not specify the relevance of the coefficients of the PDD function to the water distribution network, therefore the accuracy of their results are not certain.

Wagner *et al.* (1988b) proposed a parabolic relationship for nodes operating under deficient conditions. This PDD relationship considered all three operational modes in the distribution system: the normal mode (adequate flow), the deficient mode (partial flow) and the failed mode (no flow). The nodal flows for each corresponding modes were calculated based on the expressions given below. The relationship takes the form given in Figure 4.1a.

$$q_j^{avl} = q_j^{req} \text{ (Adequate flow) if } H_j^{avl} \geq H_j^{des} \qquad (4.16)$$

$$q_j^{avl} = q_j^{req}\left(\frac{H_j^{avl} - H_j^{\min}}{H_j^{des} - H_j^{\min}}\right)^n \text{ (Partial flow) if } H_j^{\min} \leq H_j^{avl} \leq H_j^{des} \qquad (4.17)$$

$$q_j^{avl} = 0 \text{ (No flow) if } H_j^{avl} \leq H_j^{\min} \qquad (4.18)$$

Where q_j^{avl}, q_j^{req} are available and required flows respectively at the node and $H_j^{\min}, H_j^{avl}, H_j^{des}$ are minimum, available and desired heads respectively at the node.

The important aspect of Wagner's PDD function is that it is primarily dictated by the minimum and the desired head at node. The values of the minimum and the desired heads vary depending on the water distribution system characteristics and the consumers' levels of service requirements. This relationship is comparable to that of Germanopoulos' function, however the differences occur due to the variations in the coefficients. Generally equation 4.15 is assigned a coefficient of 0.5 (Wagner *et al.,* 1988b and Tabesh *et al.,* 2004). Again the relevance of the coefficient to the secondary network characteristics were not explained therefore, the accuracy of the prediction is not certain. Figure 2.4 below shows Wagner's PDD function for different values of the coefficient.

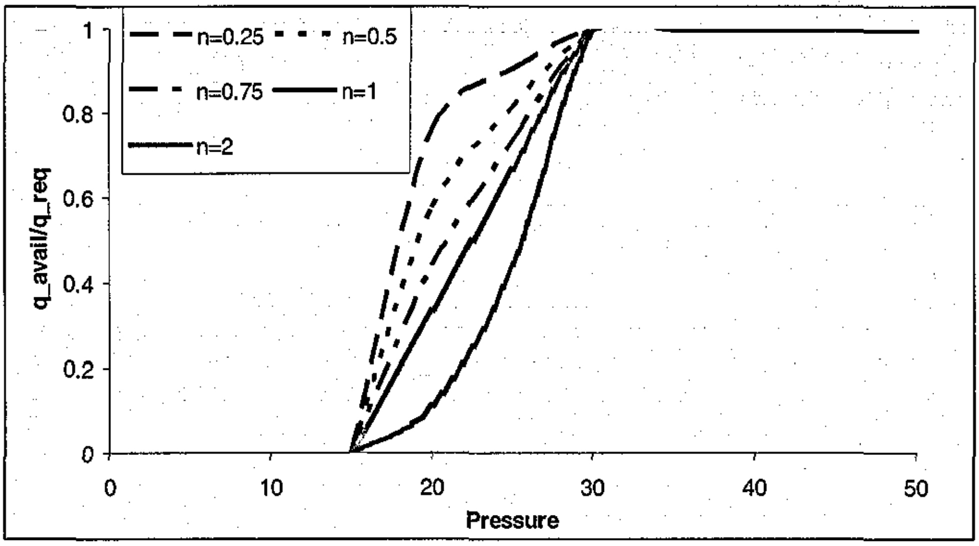


Figure 4.4: Wagners' PDD function

Where q avail is the available flow, q req is the required flow.

From the Figure 4.4 it can be observed that for low "n" values the PDD function tend to behave more like Germanopoulos PDD function where small changes in pressure result in large flow variations. However, increasing the value of "n"results in gradually varying PDD curves. Similar to other PDD functions, the shortcoming associated with this relationship is the evaluation of appropriate value for "n". This can only be achieved by calibrating the functions with field data. This would be a very tedious exercise as the coefficients are node specific.

Wagner predicted the nodal outflows of deficient networks by applying the PDD relationship retrospectively to selected nodes hence both pressure and outflows were not simultaneously satisfied. This approach is clearly not suitable as flow redistributions in the network are ignored. Tabesh *et al.* (2002) used a PDD relationship identical to that of Wagners'. The relationship was based on the expression below:

$$H_j = H_j^{\min} + R_j(q_j)^n \quad (4.19)$$

Unlike Wagner, Tabesh derived the PDD expression from the above relationship and incorporated the function with the network analysis program. The nonlinear governing equations were solved by Newton Raphson method, efficiency of the program was improved by incorporating a step length adjustment parameter. The advantage of this method over Wagner's method is that the flow distributions due to deficient conditions in the systems are simultaneously considered. However, it is widely reported that the determination of parameters n, R_j for a given network would be quite difficult in the absence of extensive field data and some form of calibration would be necessary (Tanyimboh and Tabesh, 1997; Kalungi and Tanyimboh, 2003).

Bhave (1980) introduced the node flow analysis (NFA), which is a complex iterative technique to determine partially satisfied demands at nodes. The head flow relationship used in NFA is:

$$q_j^{avl} = q_j^{req} \text{ (Adequate flow) if } H_j^{avl} \geq H_j^{des} \qquad (4.20)$$

$$0 \leq q_j^{avl} \leq q_j^{req} \text{ (Partial flow) if } H_j^{avl} = H_j^{\min} \qquad (4.21)$$

$$q_j^{avl} = 0 \text{ (No flow) if } H_j^{avl} \leq H_j^{\min} \qquad (4.22)$$

This is a discrete relationship and the values of the partial flows are not explicit. Nodal heads and the corresponding flows are obtained by solving expressions 4.20-4.22 iteratively. The demand driven conventional network analysis method is used in the iteration. This method does not employ any PDD functions and therefore, does not incorporate the secondary network behaviour when evaluating the pressure dependent flow.

Gupta and Bhave (1996) applied different PDD functions (Germanopoulos, 1988 and Wagner *et al.*, 1988b) along with NFA techniques. The coefficients of the PDD functions were obtained by regression analysis. They concluded that Wagners' function along with the node NFA provided better results than the other functions. The shortcoming in this method is that coefficients of the function cannot be related to the secondary network behaviour.

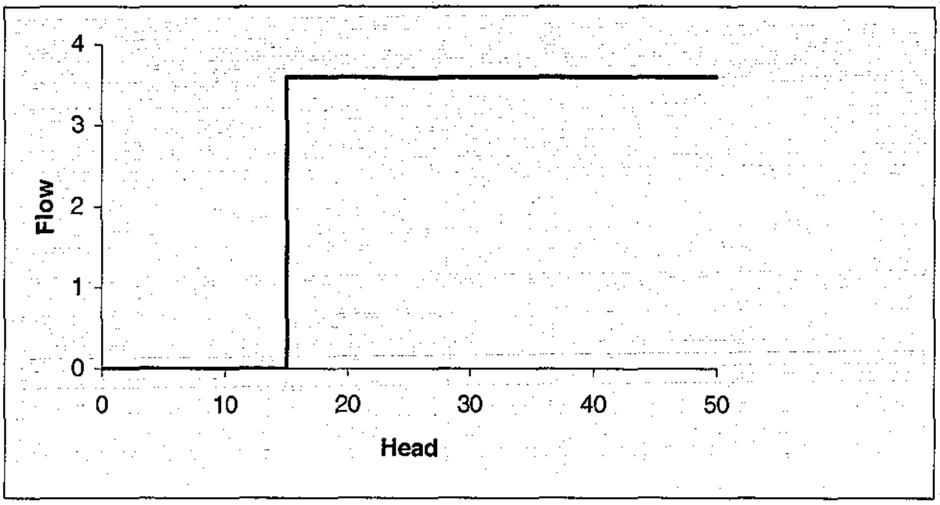


Figure 4.5: NFA relationships

Fugiwara and Li (1998) employed a differentiable function proposed by Fujiwara and Ganesharaja (1993) to simulate the pressure dependent nature of deficient networks. This function is based on the expected served demand and takes into account the insufficient heads and flows at nodes. The relative effectiveness of the nodal head, which is the ratio of available and required flows, is defined by a function of nodal heads taking values between 0 and 1. The value of the function is zero below the minimum head and one above the desired head. The nodal hydraulic availability or the available nodal flow is evaluated using the expressions given below. Figure 4.6 illustrates the functions described by the expressions below.

$$\rho(H_j) = 0 \text{ If } H_j^{avl} \le H_j^{\min} \tag{4.23}$$

$$\rho(H_j) = \frac{\int_{H_j^{\min}}^{H_j^{avl}} (z - H_j^{\min})(H_j^{des} - z)dz}{\int_{H_j^{\min}}^{H_j^{des}} (z - H_j^{\min})(H_j^{des} - z)dz} \quad \text{If } H_j^{\min} \le H_j^{avl} \le H_j^{des} \tag{4.24}$$

$$\rho(H_j) = 1 \quad \text{If } H_j^{avl} \ge H_j^{des} \tag{4.25}$$

$$Q_{avl} = \rho(H_j) Q_{req} \tag{4.26}$$

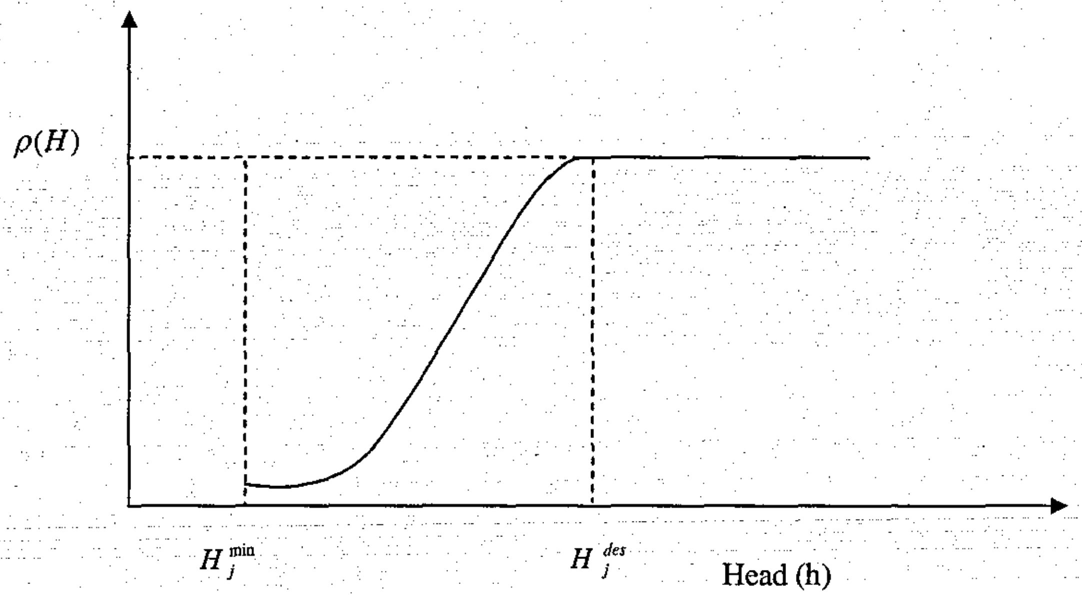


Figure 4.6: Fugiwara's function

The above expression does not seem to reflect the network characteristics or show any indication of any relevance to the network behaviour. However, the PDD relationship shows characteristics of the previous PDD functions where the pressure dependent nature is displayed between the minimum and desired nodal heads. The function is likely to have discontinuities in the event of integrating the relationship with the network analysis program.

Tanyimboh *et al.* (2001) developed an alternative method to PDD functions called source head method to predict the pressure dependent demand. Their method was based on demand driven analysis. This method assumes that the deficiencies in pressure in water distribution systems have localised affects in the vicinity of a failed component or in the area where there is excessive demand (Gupta and Bhave, 1996; Tanyimboh and Tabesh, 1997).

Tanyimboh *et al.* (2001) stated that the flows in looped distribution systems are directed in such a way that the total energy loss is minimised. Tanyimboh and Templeman (1992) observed that the small pipes which experience high head losses usually carry little flow when there are multiple paths in the system. Therefore, areas with high head losses (where insufficient pressure is prevalent) act as final destination points rather than transit points through which flows pass through to other areas of the network .

Tanyimboh *et al.* (2001) also mentioned that when a system with insufficient pressure is analysed using demand driven method, it is necessary to adjust the flows at minority of nodes with low pressures, knowing that the performance of the rest of the nodes will be mostly satisfactory.

Therefore, equation 4.19 is used to relate the heads at the node to outflows. After mathematical manipulation the available flow at the node is given as:

$$q_j^{avl} = q_j^{req} \quad \text{if} \quad H_s \geq H_{s,j}^{des}, \forall j \tag{4.27}$$

$$q_j^{avl} = q_j^{req} \left(\frac{H_s - H_{s,j}^{\min}}{H_{s,j}^{des} - H_{s,j}^{\min}} \right)^n \quad \text{if} \quad H_{s,j}^{\min} \leq H_s \leq H_{s,j}^{des}, \forall j \tag{4.28}$$

$$q_j^{avl} = 0 \quad \text{if} \quad H_s < H_{s,j}^{\min}, \forall j \tag{4.29}$$

$$H_{s,j}^{des} = H_s - H_j + H_j^{\min} \tag{4.30}$$

Where q_j^{avl}, q_j^{req} are available and required flow at node j, H_s is the head available at source, $H_{s,j}^{\min}$ is the head at source below which outflow at node j will be unsatisfactory or zero, $H_{s,j}^{des}$ is the head at source above which demand at the node would be fully satisfied, H_j is the head at node j, $H_j^{\min}$ represents the minimum head at node j which can be approximated to the elevation of node and n is the exponent whose value vary between 0.5-0.67, and can be evaluated by calibrations.

The minimum head at source for node j ($H_{s,j}^{\min}$) can be found by trial and error using simulation or field tests, which are time consuming. However, Tanyimboh *et al.* (2001) approximated the $H_{s,j}^{\min}$ to the source head above which the outflow just begins at any node ($H_s^{\min}$) and also $H_s^{\min}$ is selected such that it is above the minimum delivery head for any node thus:

$$H_s^{\min} > \min\langle H_j^{\min}, \forall j \rangle \approx \min\langle elevation_j, \forall j \rangle \tag{4.31}$$

Therefore, the modified expression for the actual flow is given as:

$$q_j^{avl} \approx q_j^{req} \left(\frac{H_s - H_s^{\min}}{H_{s,j}^{des} - H_s^{\min}} \right)^n \quad H_s^{\min} \leq H_s \leq H_{s,j}^{des}, \forall j \tag{4.32}$$

Tanyimboh *et al.* (2001) found that the approximation given above is non conservative (over estimate the nodal outflow with short fall in head). This effect is expected to be minimal since only a small number of nodes are being considered due to the localised effects of failure.

The equation 4.31 given above resembles that of Wagner *et al.* (1988b), however the only difference is that this expression considers source head instead of nodal heads. This constitutes a problem when there are more than one source supplying water to the distribution system. The estimation of source head will be a difficult process as the heads corresponding to each and every source would need to be identified. Moreover, the predicted flows would be approximate values. Therefore, the suitability of Tanyimboh *et al.* (2001) PDD method is not certain.

4.4.2 PDD Functions for Intermittent Systems

Lam and Wolla (1972) considered the scenario where the nodal draw-offs are not always fixed. They suggested that draw-off at each node depends on the head at the nodes. This is expressed as follows;

$$q_L = F_L(H_L) \qquad (4.33)$$

q_L is the outflow from the system, H_L is the pressure head and F_L is the load factor. The relationship given by 4.33 is said to describe the loads as variable loads. The study further stated that in computer simulations, the characteristic of variable loads is assumed to have the following form:

$$q_L = A_L - B_L H_L^{c_L} \qquad (4.34)$$

In which A_L, B_L and C_L are appropriate constants dependent on network characteristics.

Equation 4.33 takes the form of a power relationship. The expression suggests that even if there is no pressure head at the node, there will be a finite flow available at the node. However, appropriate selection of the coefficients will result in a power relationship (orifice flow).

Chandrapillai (1991) proposed a relationship for the pressure dependent demand at nodes. This relationship was applied to household with overhead tanks. He stated that in intermittent systems, consumers will try to collect as much water as possible. The main assumption in this method is the consumers are active throughout the supply duration.

The basis behind this method is that the nodal supplies from each node depend on the inherent system characteristics such as the diameter, length, roughness, connectivity, elevations, demand and the downstream conditions of each node. In other words, adjustments in system characteristics such as the rehabilitation and replacement of components (pipes and valves) will contribute to the equitable supply of water to the consumers. The nodal outflows are obtained by an iterative process and are given below.

$$H_j^{des} = H_j^{\min} + R_j (q_j^{req})^n \qquad (4.35)$$

$$q_j = q_j^{avl} - \frac{H_j^{\min} + R_j (q_j^{avl})^n - H_j^{des}}{nR_j (q_j^{avl})^{n-1}} \qquad (4.36)$$

Where $H_j^{des}, H_j^{\min}, H_j$ are the required, minimum and available heads respectively at nodes, R_j is the resistance constant for the system, n is the exponent, q_j^{req} is the flow required at node, q_j^{avl} is the previous value of nodal outflow and q_j is the updated outflow for nodes with less than fully satisfactory pressure

Nodal outflows given in Chandrapillai (1991) are corrected depending on the available and the required heads at the nodes. That is when $H_j^{\min} < H_j < H_j^{des}$, the available flow q_j is given by equation 4.36, if $H_j < H_j^{\min}$ then the available flow $q_j = 0$, when $H_j > H_j^{des}$ the available flow becomes the desired demand.

According to Chandrapillai's relationship the consumer outlet will have a constant flow rate when the head at the node is above the desired head. This characteristic of the PDD function contradicts the behaviour of uncontrolled outlets such as stand pipes in intermittent systems. Those outlets are free flowing outlets and are characterised by the orifice flow (Vairavamoorthy, 1994; Akinpelu, 2001). However, the relationship is applicable to systems with overhead tanks and sump tanks.

Akinpelu (2001) illustrated this method by assuming a consumer connection that supplies the water from the distribution main to an overhead tank (OHT). As illustrated in Figure 4.1a the OHT is fed only when the pressure head at the tapping point is above the static lift (h_l) which is the level difference between the distribution main and the OHT.

The network characteristics considered in Chandrapillai's function are represented by the coefficients of the PDD function. However, when it comes to the determination of PDD coefficient this PDD relationship has the same problems as that of previously mentioned ones. Furthermore the PDD relationship assumes that once the head in the network reaches the desired head, nodal outflows will not be sensitive to pressure. This assumption is not applicable to water starved systems as the consumers in such system tend to keep the outlets open throughout the supply period (Vairavamoorthy, 1994; Akinpelu, 2001). Therefore, care should be taken when applying this relationship to intermittent systems.

A head-discharge formulation based on orifice function (equation 4.36) was given by Reddy (1990); Vairavamoorthy (1994) and Akinpelu (2001). These formulations were applied to simulate the behaviour of intermittent systems where outlets are free flowing and wholly dependent on the residual heads. Akinpelu (2001) combined the PDD function with queuing process to simulate the activities of free flowing outlets where there is some control due to increased quantities of water. However, he observed that the system becomes most vulnerable when all the outlets were discharging simultaneously (outlets become free flowing), hence the assumption of orifice flow is still appropriate.

$$q = AH^n \qquad (4.37)$$

Where q is the nodal outflow, A is the coefficient of the function which depends on the outlet coefficients and n is a constant for particular outlets.

Vairavamoorthy (1994) and Akinpelu (2001) obtained the coefficients of equation 4.37 by analysing the secondary network behaviour. The nodal outflows predicted using the above relationship has no upper limit as shown in Figure 4.1b. For higher residual heads in the network, (higher than the desired head), the outflows can be significantly larger than the required demand. The outflow is sensitive to the values of the coefficient hence it is very important to evaluate them accurately. The application of the power relationship (orifice function) is more appropriate for intermittent systems than that proposed by Chandrapillai. The power relationship is applicable to systems with both free flowing and controlled outlets.

4.4.3 Strengths and Weaknesses of PDD Functions

PDD functions are a convenient tool to analyse pressure deficient networks. The functions can be easily incorporated with the network analysis and solved using one of many solution methods (such as Newton-Raphson method, linear theory method or gradient method) as described in the section 4.2.2. The accuracy of predicting the pressure dependent demand depends on how well the PDD function represents the network characteristics. The shortcomings associated with each function are described individually along with the description of functions in previous section.

In general the deficiencies associated with the PDD functions are their inability to explicitly relate the secondary network (the area which is supplied from the primary node) characteristics. However, the coefficients associated with the PDD functions implicitly represent the secondary network behaviour. Therefore, determinations of the PDD coefficients play a major role in the use of the PDD functions with network analysis. The secondary networks corresponding to the WDS nodes are not similar, as a result the PDD coefficients are node specific. Hence determining the coefficient will be a time consuming as well as an intensive process. Once the coefficients of the functions have been determined, they need to be calibrated to make sure they simulate the field conditions.

Another issue that must be noted with PDD functions is that they are not sensitive to variations in the consumer demand behaviour. For example the PDD function predicts the demand or the flow into a node in the distribution system assuming that all the consumers are active at a particular time period. However, when a part of the consumers (say 50%) are inactive, the PDD function should predict a lower value for the nodal demand as only half the consumers are active at the node. The predicted flow will be for the entire population at the node, in other words the nodal demand is over estimated.

The variation in the number of consumers accessing the supply will also have an impact on the PDD coefficients. Even though the above mentioned scenario may hardly occur in WDS, such events restrict the prediction capability of the PDD function.

This situation can be remedied by analysing the characteristics of the PDD functions for different demand values at a node and obtaining corresponding coefficients using field data and calibration. This will result in a PDD function for a particular node having a set of coefficients for different demand situations (peak times, off peak times etc.). This will add additional complexities the PDD functions.

The nodal flows predicted by the PDD functions depend on the range between the minimum and desired heads at the node (Tabesh *et al.*, 2004; Wagner *et al.*, 1988b). Therefore, it is very important to determine the exact boundary values of the heads which are based on minimal and desired residual pressure at the consumers' outlets. This information is usually available in standard codes of practices. The OFWAT specified residual pressures are 7m minimum and 10m desired pressures. These values need to be translated to the primary node which represents hundreds of households.

Furthermore, discrete PDD relationships given by Wagner *et al.* (1988b), Chandrapillai (1991), Tabesh *et al.* (2004) will have a problem of encountering discontinuities when integrating with the network analysis program.

Therefore, the methods that are capable of over coming the insensitivities and short comings of the PDD functions must be developed. This is achieved by using micro level models as described below.

4.5 Pressure Dependent Demand Modelling with Micro Level Models

In this research, the method based on the micro level modelling of the WDS is proposed. As the name implies, this method looks into the detailed analysis of the WDS. This is based on simulating the behaviour of each and every individual consumer nodes (secondary nodes). In this thesis this method is referred to as micro level modelling.

In this section, the micro level modelling of WDS to represent the pressure dependent behaviours of the demand nodes is presented. Motivation for the micro level modelling to simulate the pressure dependent demands originated from the use of secondary networks to lump the individual consumer outlets in intermittent supplies (Vairavamoorthy, 1994; and Akinpelu, 2001). In intermittent systems consumer outlets are modelled as orifices whereas in the proposed method individual households are represented by overhead tanks coupled with a ball valve to control the inflow from the WDS.

4.5.1 Proposed Micro Level Modelling of WDS

The micro level models (MLM) proposed in this thesis simulates the pressure dependent demand behaviour of the water distribution networks without the use of PDD functions. This has been made possible by representing the actual WDS behaviour upto individual consumer level using MLMs. The MLM represents the internal piping arrangements of the households. An insight into the internal piping arragements of individual households is given in the section 4.5.1.1.

4.5.1.1 Piping arrangements of household

One of the factors that has a significant effect on the water usage among consumers is the household piping arrangement. In continuous supply systems usually households are connected to the WDS through an overhead storage tank (the UK system) or a direct connection (European system) (Field, 1978; Vairavamoorthy, 1994). Whereas, in intermittent supplies, households are connected through sump tanks or yard taps.

The primary difference between the UK and the European systems is that the first one is connected to the distribution main through an overhead storage tank coupled with a Portsmouth ball valve to control the inflows. The second arrangement doesn't have the storage tank. Both systems react differently to pressure variations in the distribution system.

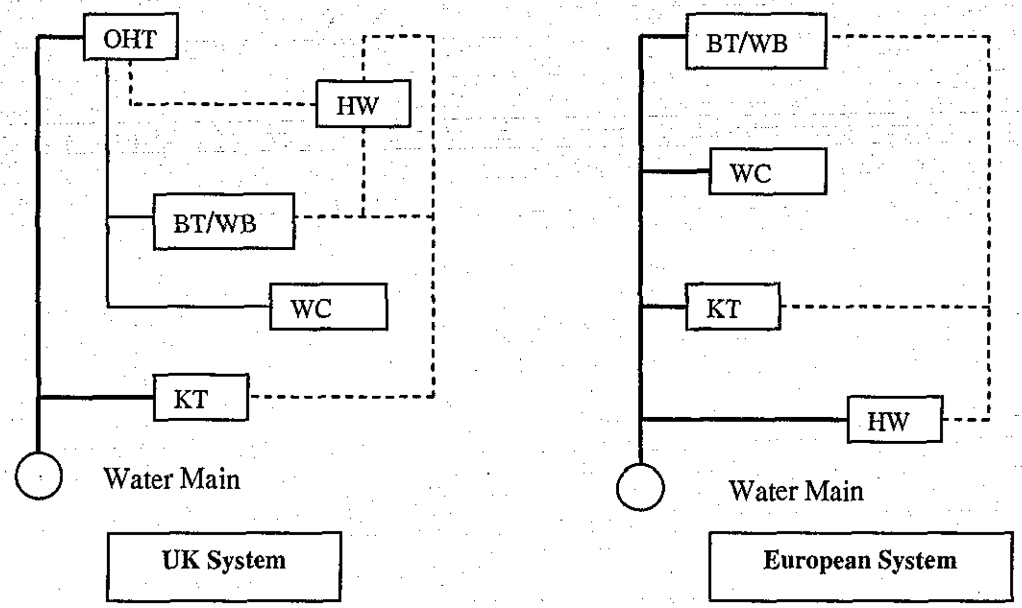


Figure 4.7: UK and European household piping arrangement

OHT - Over Head Tank, HW - Hot Water, BT/WB – Bath Tub/Wash Basin, WC – Water Closet
KT – Kitchen

Water Main
Hot Water
Cold Water

Sump tank and yard taps are analogous to the UK and the European systems respectively where sump tank is an OHT with zero elevation and the yard tap represents the direct connection to the household. In the event of pressure deficient situations, flows in both the UK and the European systems become pressure dependent. This is explained below.

In both the systems flow rate at any instant to a group of consumers depends upon the number of households drawing water and their corresponding rates of flow. In the UK system the OHT will receive a reduced flow when there is a reduction in system pressure. The flow into the OHT is dictated by the system pressure, the consumer behaviour is reflected by the response of the ball valve to the water level in the tank. The OHT is capable of sustaining the supply to the consumers when there is a pressure deficiency in the system for a short period of time. On the other hand pressure deficiencies in European type systems will immediately impact the supply to the consumer. If low pressure situations persist for longer durations, the OHT in the UK system will not be able to sustain the flow and pressure, instead will behave like the European system.

4.5.2 MLM Development

The basic concept of micro level modelling proposed in this study is based on simulating the behaviour of individual households as pressure dependent outlets and then introducing this into pressure dependent analysis. However, since there are a large number of households, it is impossible to simulate the behaviour of individual households and incorporate those into analysis. Therefore, these households are lumped together based on the homogeniety at the secondary nodes and then evaluating equivalent dimensions of the lumped nodes (equivalent tank dimensions and lumped demand profiles) which are used in the simulation of MLM.

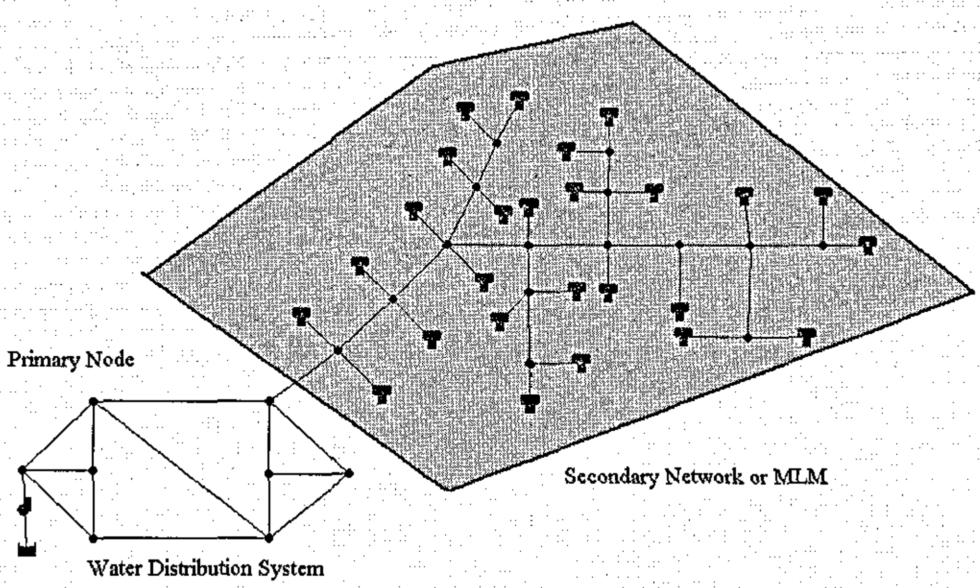
The development and the simulation of MLMs are the primary activities in analysing the pressure dependent demand nature of the WDS without the assistance of the PDD functions. The steps involved in the MLM methodology are listed below.

- Identifying the MLM structure.
- Eavaluating the equivalent tank dimensions.
- Obtaining the lumped demand profiles.
- Simulating the PDD behaviour.

4.5.2.1 Identifying MLM structure

Reddy (1990) reported that in large networks catering to urban areas, consumers are usually served by small tree networks which are called secondary networks(or Micro Level Models). The main feeding network is called the primary network. Generally secondary networks consist of small diameter pipes compared to the primary network. Reddy (1990) suggested that parts of network that have pipe diamteres of 100mm and less can be considerd to be the secondary network. The area served by the secondary network must be selected based on expert judgement and experience. The modeller's experience is complemented by the use of a rational approach such as the Voronoi polygon method to define the area as is given in Akinpelu (2001). The methodology for generating Voronoi polygons to define the secondary network areas is described in Appendix 2.

It has been argued that in determining the characteristics of the secondary networks, the dead ends are necessary in order to capture the cumulative outflows from the primary node (Reddy,1990). It is possible for a secondary network to abstract water from a primary node elsewhere in the network, hence it will not be correct to say that the total demand is satisfied from the node under consideration. However, it has been reported in the water practice manual (IWES, 1984) that most networks are insensitive to small changes in demand between one node and another. Moving a small demand from one node to another will have a very insignificant effect on the system pressure. Therefore, the micro level models are developed as tree networks without loops.



(Not to scale)

Figure 4.8: A Typical Micro Level Model (Fed from a primary node)

Micro level models are identified by observing the area supplied from the primary nodes of WDS. Figure 4.8 shows a typical MLM. The tree shaped network (shaded area) which is fed from a primary node represents a MLM. Each overhead tank in the network represents the consumers served by the MLM.

A primary node of a WDS supplies to hundreds of households in the area covered by the correponding secondary network. Representing all the consumers in the MLM is unrealistic therefore, the households with similar elevations are lumped together using Voronoi polygons as given in Akinpelu (2001).

The lumping of households mainly concerns aggregating the demands and dimension of the overhead tanks.The demands of lumped individual households are added together to obtain the lumped demand of the secondary network node. The secondary network nodes will have equivalent OHT that represent the collective capacity and the charecteristics of the (lumped) individual households. The methodology in determining the equivalent tank dimensions is given in section 4.5.2.2 below.

Once the equivalent OHT dimensions are evaluated, the dimensions of the service pipes that supply to the lumped node need to be determined. The equivalent service pipe dimensions are determined based on the collective carrying capacities of the service pipes of individual households and is described below in section 4.5.2.2.

Once the lumping process is carried out, the MLM will have a manageable number of consumer outlets representing the acutal number of consumers in the MLM.

The lumping process used in this thesis is based on the following criteria given below . This was followed in order to maintain the consistency during the lumping process.

- A maximum of 50 households were lumped into a single secondary node.
- The maximum elevation difference between any two households in a Voronoi polygon was selected to be 5m.

The headloss in the service pipes connecting the households are small (Reddy,1990). However, having an upper limit to the number of lumped households will help maintain the consistency in the headloss between the lumped nodes. In other words, the maximum headloss between the households in a lumped node is the headloss between the 1^{st} and the furthest (50^{th}) household. Lumping too many households together will compromise the detail in representing the behaviours of the households.

The elevation difference between two households is kept at 5m inorder to avoid large pressure variations in between the nodes that are being lumped.

4.5.2.2 Evaluating equivalent tank dimensions in MLM

Micro level networks describe the WDS in greater detail, including the individual residential service pipes. Although the extent of detail is supposed to provide accurate results, accuracy and the amount of effort required to model the system are not proportional.

The aim of lumping a MLM is to simplify the network in terms of size and complexity. When representing the lumped consumer outlets, service pipes feeding individual consumers are replaced by equivalent service pipes. The head losses in the service pipes are assumed to be negligible.

Equivalent pipes can be obtained by considering carrying capacities of each pipe. Anderson and Al-Jamal (1995) proposed an element-by-element approach to obtain capacities of equivalent pipes. They considered the Hazen Williams head loss relationship, which is given below.

$$\Delta H = KQ^{1.852} \qquad (4.38)$$

or

$$Q = G\Delta H^{0.54} \qquad (4.39)$$

Where ΔH is the head loss at the link, K is the pipe resistance, G is the pipe conductance.

For, i series pipes of resistance K_i. The equivalent resistance is given by:

$$K_{equ} = \sum K_i \qquad (4.40)$$

and for i parallel pipes the equivalent conductance is given by

$$G_{equ} = \sum G_i \qquad (4.41)$$

Once the consumer outlets in the MLM are lumped and equivalent pipe dimensions have been evaluated, it is essential to determine the equivalent plumbing arrangements for the lumped nodes. The important component of the plumbing arrangement in the UK households are the overhead tank. The tanks are of average height 0.75m and have an area of 0.54 square metre (Field, 1978).When determining the equivalent tank dimensions, the tank height is maintained at

0.75m, inorder to represent the variations that occcur in individual households. The area of the equivalent tank is determined using the expression given below.

$$D = 2\sqrt{\frac{nA}{\pi}} \qquad (4.42)$$

Where D is the diameter of equivalent tank, A is the area of a household tank (assumed to be $0.54m^2$), n is the number of households lumped together in a polygon.

4.5.2.3 Residential water use

To obtain the usage profiles of the lumped nodes in the MLM, individual usage profiles of the consumers and how the consumers access the water distribution system must be known. The following section gives an insight into the types of consumers and their water usage.

The main types of consumers in a WDS are household users, industrial users and public consumers (hospitals, fire fighting etc). Apart from the above mentioned consumptions, water is also lost due to leakage and illegal connections (unaccounted for water). In this research the component of unaccounted for water is integrated into the consumers' usage as a percentage of demand for the sake of simplicity. This approximation will have a very minimal effect in the modelling process. Each of the above mentioned types of consumers have different usage patterns. The household consumption has the most uncertain parameters and unpredictability. Therefore, it is appropriate that the household water usage is analysed first in this section.

It has been observed that the household consumption can be categorized into two volumetric or deterministic use and time dependent or stochastic use (Vairavamoorthy, 1994, Obradovic and Lonsdale, 1998). The volumetric consumption constitutes the instances where a specific volume of water is required as in filling a bath, using a kettle, the washing machine and the WC. These uses will not be affected by the slight pressure variations in the system. In time dependent consumption, water is required for a specific period, for example having a shower, washing the car etc., the quantity of water consumed in these types of consumption very much depends on the system pressure. For example, a person hosing down a car will spend the same amount of time at the job regardless of the system pressure (whether it is 15m or 25m).

Water use patterns and the sequence vary area to area depending on the lifestyle, availability of water, cultural and religious practices etc. In order to generate a household consumer demand profile or the demand profile for an area, it is important to identify the household consumer usage in terms of the frequency of use, intensity of use, the duration and their corresponding probability distributions. Field (1978), Buchburger and Wu (1995), Buchburger and Wells (1996), Alvisi *et al.* (2003), Jankovic-Nisic *et al.* (2004) all analysed the characteristics of residential water use to model the instantaneous residential demand.

Field (1978) measured the flow rates into three areas of domestic consumers as well as individual residences. The data obtained from the individual households were used to establish individual water use sequences for the households. The analysis of the flow data from the three areas showed that the flows started to increase around 5 am and reached a peak by 9am. After 9 am the flow started to reduce however, produced secondary peaks.

Using the above information Field (1978) calculated the number of consumers drawing water at each 10 seconds from the system by employing the following relationship.

$$Q_1 = N_1 q_1 \qquad (4.43a)$$

$$Q_2 = N_1 q_2 + N_2 q_1 \qquad (4.43b)$$

$$Q_i = N_1 q_j + N_2 q_{j-1} + .. + N_j q_1 \qquad (4.43c)$$

Where Q_i is the measured flow rate at time i, q_j is the calculated flow rate in the service pipe at time period j, N_i represents the number of consumers starting to use water at time period i. These calculations were done based on the following assumptions:

- The rate of flow of water started to increase at 5am i.e. the consumers started to access the water.
- All the consumers were active by 9 am.
- The peak flow occurs between 5am and 9am.

Buchburger and Wu (1995), Buchburger and Wells (1996) proposed a method to model the time series of the residential water demand by means of a rectangular Poisson pulse process. In their study they characterized the water use using three variables; the intensity, the duration and the frequency. Also water use was compared with the queuing analogy where the home occupants represent the consumers and the household appliances and the water fixtures represent the servers. In a queuing process consumers randomly arrive following a Poisson process and engage one or more servers for a random length of time.

Buchburger and Wu (1995) approximated the instantaneous water use by rectangular pulses of random duration and intensity. It was suggested that more than one pulse starting simultaneously is unlikely due to the Poisson distribution. However, it is possible for more than one pulse with different starting times to overlap for a limited duration. In such situations the total water use was evaluated by adding the intensities of the individual pulses. Buchburger and Wu (1995) demonstrated that the mean water use intensity, variance of water use intensity and utilization factor (service rate/arrival rate) are the three parameters required to model the water use of a residence.

Alvisi *et al.* (2003) developed an alternative method to model the instantaneous residential demand. They indicated that the Poisson formulation is inadequate to represent the residential demand and also they questioned the addition of individual intensities to generate the total water use.

The alternative approach proposed by Alvisi *et al.* (2003) was based on Neyman-Scott clustered point process. This method has been widely used in the simulation of rainfall events (Cowpertwait, 1996 a, b). Alvisi *et al.* (2003) illustrated that this method is more suitable for the reproduction of time series of the water demand for a small number of users.

In modeling the water consumption, the water demands from the use of household appliances and fixtures were recorded as rectangular pulses as in Buchburger and Wu (1995). The individual pulses of demand are called elementary demand (ED) and a group of aggregated elementary demands form a demand block (DB). With the Neyman-Scott clustered point process, formation of ED and DB are considered separately. The origins of the DB are represented by means of a Poisson process with an arrival rate λ_P and each DB is associated with a random number of EDs which are distributed according to a Poisson process with parameter μ_P. The origins of each ED are independently distributed whose temporal distances are distributed with an exponential distribution with parameter β_E. The temporal distance of each ED cell is represented by an exponential random variable with parameter η_E. The intensities of water use are modeled by an exponential distribution with parameter ε_E.

Jankovic-Nisic *et al.* (2004) analysed the stochastic nature of the residential water demand with respect to the frequency, intensity and duration of the use of household appliances in 28 households. Jankovic-Nisic *et al.* (2004) carried out a statistical analysis of the sum of the usage of a one particular appliance throughout the 28 household over 24 hours and concluded that a standard water usage pattern does not exist. However, from the original data set they calculated the mean of the Poisson distribution for every appliance for every hour. The chi square tests carried out on the means supported the assumption of Poisson distribution.

The consumer demand patterns were generated using Poisson distributions for each appliance and a Monte Carlo based random number generator was employed to generate the consumer demand patterns at node level.

Both Buchburger and Wu (1995) and Alvisi *et al.* (2003) demonstrated the methods to model the instantaneous residential water use. The latter method is a parameter intense technique (5 parameters) whereas the first method only requires 3 parameters. Both the methods have the capability to represent the realistic instantaneous residential water use. Jankovic-Nisic *et al.* (2004) method can be seen as an extension of the Buchburger and Wu (1995) method, where nodal demands are based on a Poisson process and also uses a Monte Carlo type method to generate the demand patterns for each time step.

The main difference between Field (1978) and the other methods described above is that the latter tried to model the dynamic variations in the water use whereas, the former assumes a static demand sequence based on observations.

The aim of the above review of the instantaneous residential water demand is to acknowledge the developments and the available methodologies to model residential demand. However, the intention in this chapter is not to accurately model consumer water use, but to use a simple demand model to demonstrate the characteristics of micro level model analysis.

4.5.2.4 Obtaining lumped demand profile

In order to simulate the WDS using a MLM, it is important to generate lumped consumer demand profiles at the nodes. To develop the lumped usage profile, individual consumer usages throughout the day should be known. In this section the individual usages are assumed based on the observations made by Field (1978).

Field (1978) only presented the morning household usage, however the evening usage included is based on observations of household use and experience. For the purpose of simplicity, the consumer usage sequences are taken to be fixed. The consumer usage sequence adopted in this thesis is as follows:

- Morning use: water closet, wash, clean teeth, kettle, shower, cleaning.
- Evening use: washing machine, dishwasher, cooking, evening wash, kettle.

Apart from the above mention morning and evening use, occasional use of the kettle from kitchen tap is also included in the individual household usage profile. The usage profile is generated based on 4 individuals per household.

Both morning and evening uses add up to 137 lpcd (Table 1), which is the average per capita consumption for Severn Trent area (OFWAT, 2007). The household usage pattern based on Field's analysis is shown in Figure 4.9 below.

Table 4.1: Components of a household water use

Water use	Flow rate (lps)	Durations (s)
Water Closet	0.145	70
Wash	0.167	50
Clean Teeth	0.09	40
Kettle	0.167	10
Shower	0.1	600
Cleaning	0.017	1200
Washing M/C(evening)	0.028	3600
Dishwater(evening)	0.017	1800
Cooking(Evening)	0.013	1500

The individual household consumption profiles need to be aggregated to obtain the lumped demand profile. The aggregation of demands has to be based on the way consumers join the water distribution system. The order in which consumers join the WDS will depend on consumers' lifestyles and habits. This also dictates the distribution of nodal demands with time.

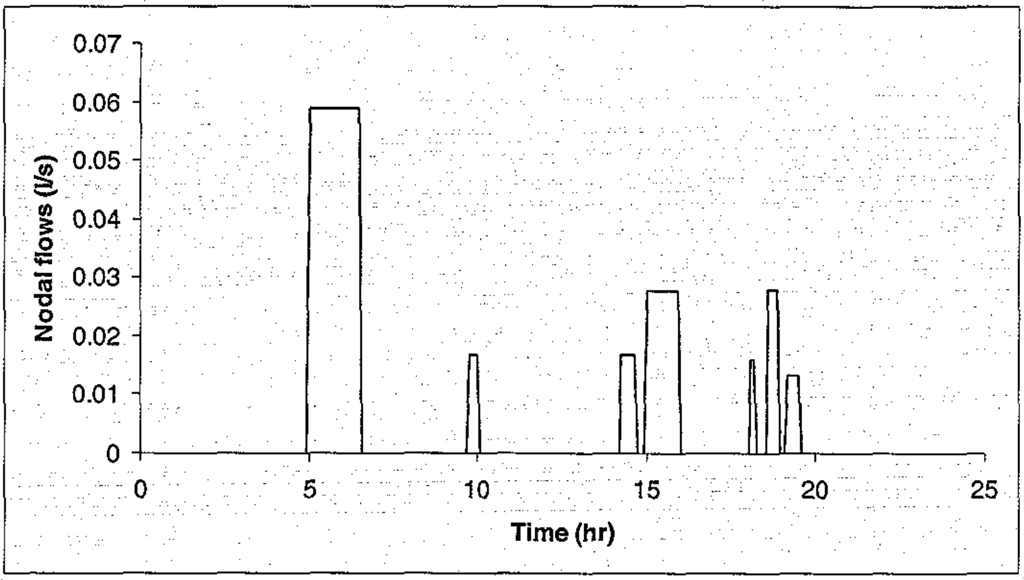


Figure 4.9: Household water use

Nodal demands in water distributions are random events, but there have been attempts to associate statistical distributions with the demands in water distribution systems. Alegre (1992) as mentioned in Jankovic-Nisic *et al.* (2004), used normal distribution to describe the variability of water consumption at nodes. Khomsi *et al.* (1996) and Tabesh *et al.* (2004) derived the nodal demand distribution from the daily system demand distribution in a region in the Southwest England during the period of (1976-1989). Sensitivity analysis carried out on the data revealed that the normal distribution is the closest. Similarly Xu and Goulter (1998) assumed that the nodal demands, reservoir levels and pipe roughness coefficients are normally distributed variables. In the above mentioned studies the consumer water usage throughout a specified period was shown to be normally distributed. They did not specify any indication of how consumers join the water distribution system but only highlighted the distribution of demand. However, in this section, the way in which consumers accessing the water distribution system is modeled.

The lumped demand profile at the node is generated based on the assumption that consumers join the water distribution system in a normally distributed manner. The basis behind this assumption is obtained from the observations made by Field (1978).

Field (1978) measured the water usage for an area and also obtained the flow rate at consumers' service pipes which are shown in Figures 4.10 and 4.11 respectively. Along with these flow rates and equations 4.43 a, b and c, the number of consumers joining the distribution system were determined. Number of consumers accessing the water distribution at every one minute interval was determined and shown in Figure 4.12. A theoretical distribution with mean of 11minutes and a standard deviation of 5.5 has been fitted to demonstrate the normally distributed behaviour of consumer access.

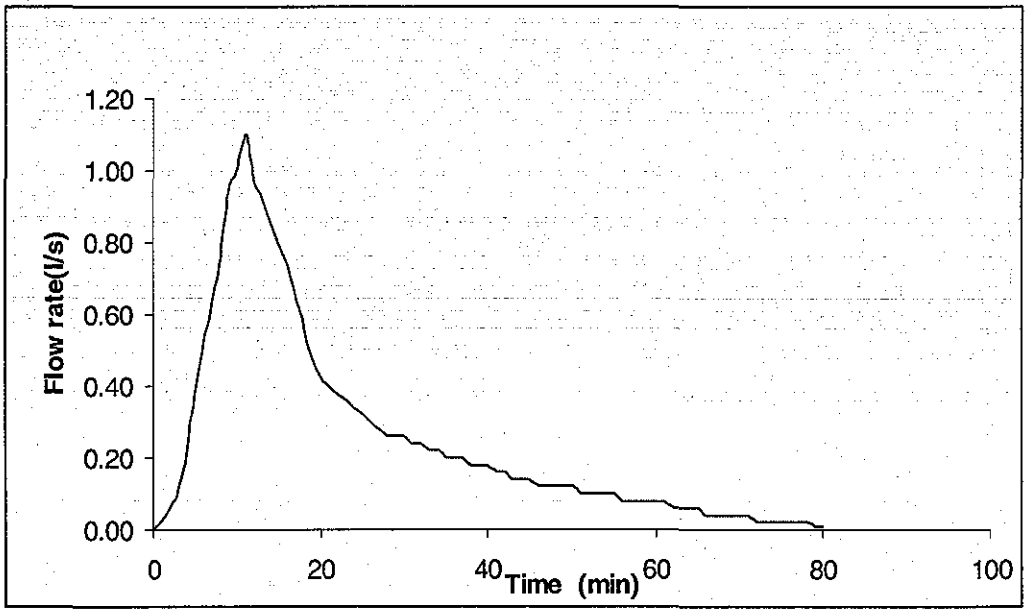


Figure 4.10: Measured flow rate to an area (Field, 1978)

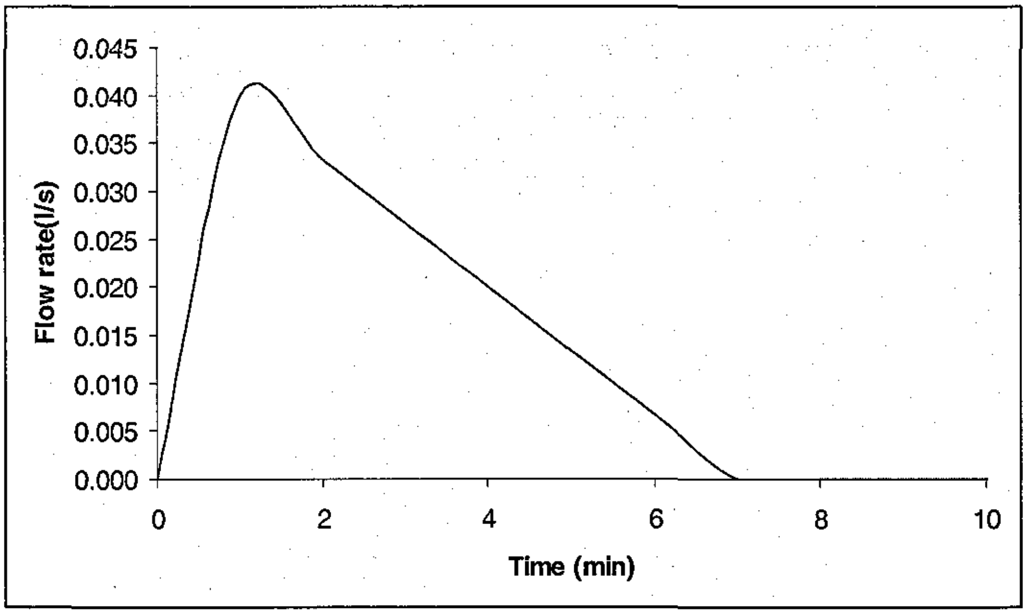


Figure 4.11: Calculated flow rates at the service pipe (Field, 1978)

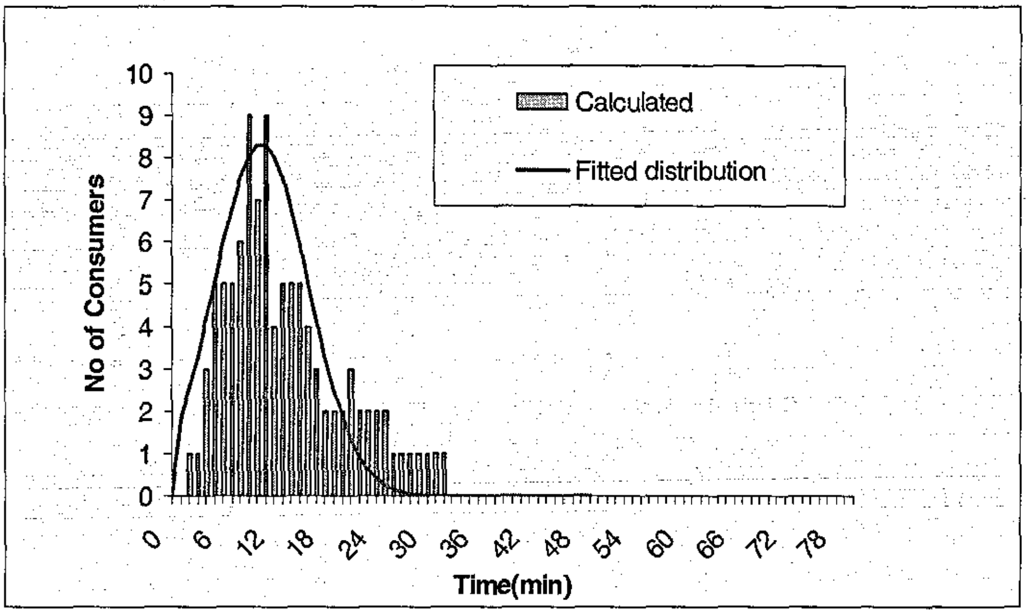


Figure 4.12: Consumers' water access based on Field (1978) data

Figure 4.12 indicates that the number of consumers accessing the WDS can be modeled using a normal distribution. This has been derived based on a small set of data. However, in order to generalize the assumption of normally distributed consumers' access of the WDS, further investigations based on a large set of data are needed.

In this instance the rationale for the assumption of normal distribution when generating consumer demand profiles is obtained from the derivation of Field (1978) observations shown in Figure 4.12. Based on the analysis of Field (1978) data set, the lumped demand profiles of the nodes were generated assuming that the consumers join the WDS in a normally distributed manner. In other words the consumers are assumed to start the usage at 5am with a mean at 7am and a standard deviation of 2hrs, therefore the maximum number of consumers will be accessing water at 7 am.

The usage profile of a lumped secondary network node with 50 households and a primary network node with 600 households are shown below in Figures 4.13 and 4.14 respectively. These usage profiles have been developed based on the individual household usage profile shown in Figure 4.9 and assuming a normally distributed demand behaviour as mentioned above.

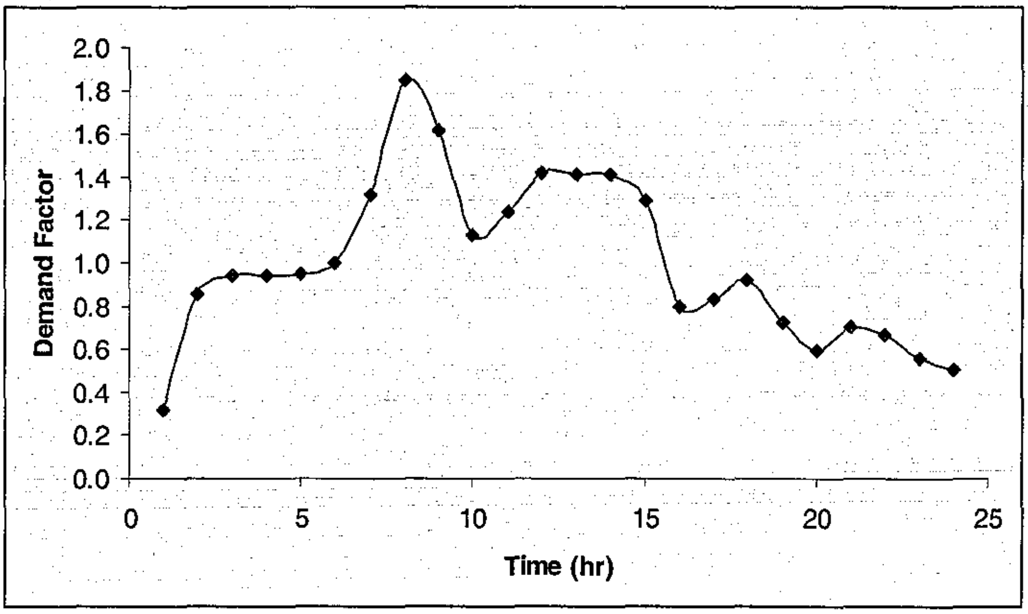


Figure 4.13: Usage profile for 50 households (secondary node)

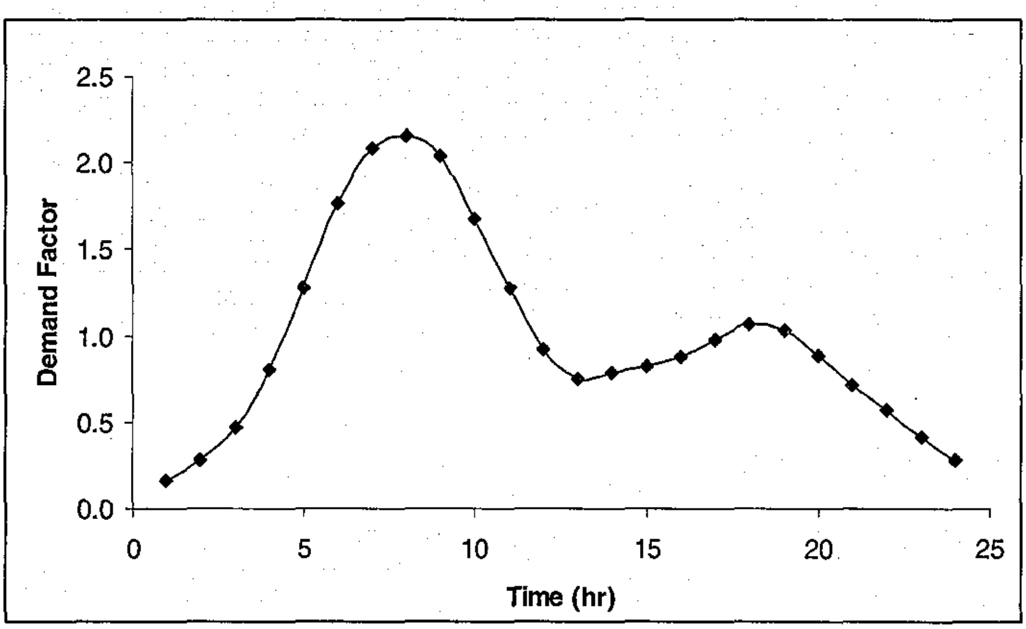


Figure 4.14: Usage profile for 600 households (primary node)

4.5.2.5 Simulating PDD behaviour

In order to smulate the pressure dependend demand nature of the WDS using MLM, their behaviour need to be appropriately represented. In other words plumbing arrangements in the households and the associated control mechanisms should be incorporated to the micro level model. The dimensions of household tanks and demand profiles can be obtained as explained in the previous sections. The action of ball valve attached to the over head tank to control the flow can be modelled using level control switches coupled with the pipe supplying the OHT. Figures 4.15 and 4.16 below show the secondary network (MLM) with inherent plumbing arrangement and the overhead tank arrangement respectively.

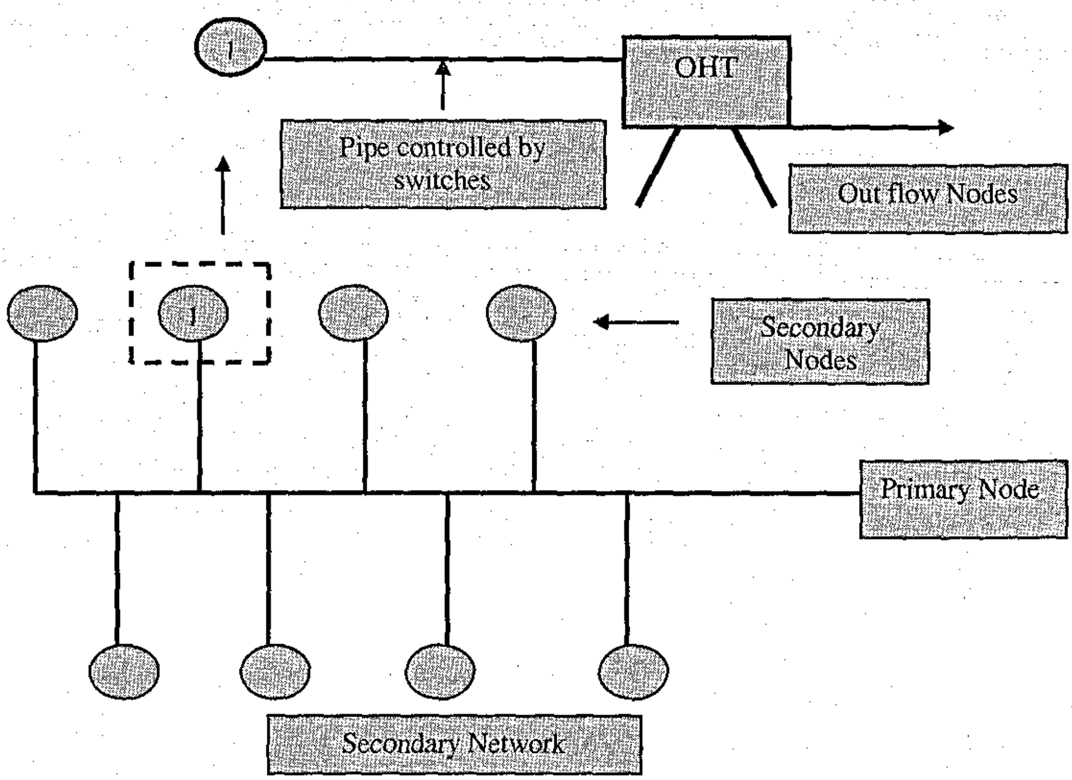


Figure 4.15: Micro level models (secondary nodes represented by overhead tanks)

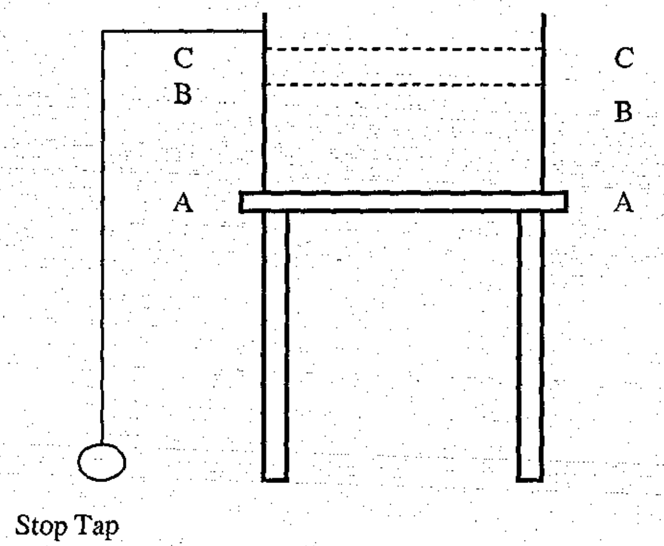


Figure 4.16: Overhead tank of a household

AA – Bottom water level at the OHT

BB – Level at which ball valve becomes active

CC – Top water level at the OHT

Water flows from the stop tap through the pipe to the overhead tank. Flow depends on the head difference between the stop tap and the overhead tank. The flow into the overhead tank in the MLM is dictated by the head flow equation given below.

$$H_S - H_T = KQ^2 \qquad (4.44)$$

Where H_S is the head at stop tap, H_T is the head at the inlet of the OHT, K is the carrying capacity of the pipe that carries the flow from service pipe to the tank, Q is the flow into the OHT.

When the water level at the OHT is below the level BB, there will be no head at the OHT inlet (i.e. $H_T = 0$). Therefore, the flow in to the OHT will have the form:

$$Q = \sqrt{\frac{H_S}{K}} \qquad (4.45)$$

The water level at the OHT varies between the levels "BB" and "CC" ball valve in the tank starts to operate, enforcing a resistance to the flow into the tank. Hence the flow into the tank becomes:

$$Q = \sqrt{\frac{H_S - H_T}{K}} \qquad (4.46)$$

Where $(H_S - H_T)$ is the head loss due to the resistance in the pipe and ball valve. When "BB" approaches "CC", the value of $(H_S - H_T)$ decreases until water level reaches the level "CC" in the tank. At this point the head loss at the ball valve exceeds the head at the stop tap, forcing a no flow situation.

Pressure deficiencies in the system will affect H_S therefore, the flow into the OHT will depend on the system pressure. However, the ball valve controls the flow into the OHT based on the household usage. Characteristics of a Portsmouth ball valve are shown in Figure 4.17 below.

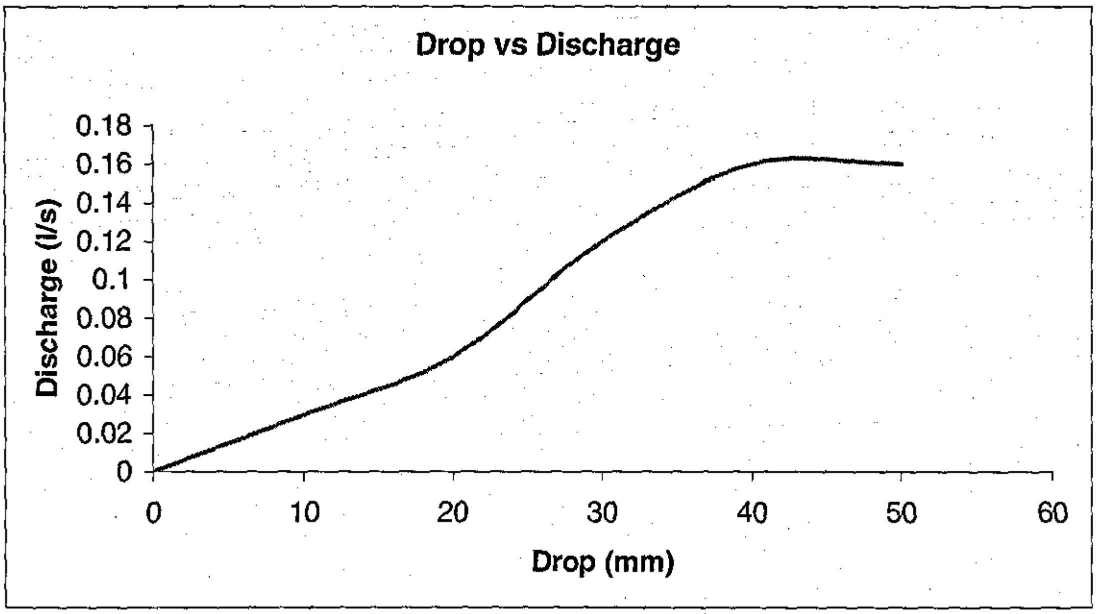


Figure 4.17: Portsmouth ball valve characteristics

Four different scenarios can occur when analysing the flows into the OHT. This explained below in Figure 4.18.

Normal operation without household activity: In this situation the system has adequate pressure but the flow into the OHT is nil as there is no consumer activity hence the ball valve is closed.

Normal operation with household activity: As consumers draw water from the OHTs, ball valve opens and there will be a flow into the tank from the system, the quantity of flow will be equal to the usage and the rate of flow into the OHT will be high.

Pressure deficient situation without household usage: Due to the deficiency in system pressure, head which supplies to the OHT will be reduced. However, as there is no consumer activity ball valve remains closed hence no flow into the OHT.

Pressure deficient situation with household usage: When there is consumer activity during a pressure deficient situation in the network, rate of flow into the OHT will be slower than what consumers draw from the tank. Therefore, pressure at consumers' outlet will be reduced. The situation will be aggravated if the WDS experiences prolonged pressure deficiencies and the consumers continue to draw water. In such situations consumers may be faced with a situation where they will experience very low pressures due to lack of water in the OHT.

There will be two separate situations where no flow will pass into the OHT. The first one being the OHT becoming completely filled up and the second is when the head at the stop tap is insufficient to overcome the head loss in the pipe, in other words H_S is not sufficient to raise the water up to the OHT.

OFWAT (2005) has specified that the minimum head required at consumers stop tap is 7m this would be sufficient to raise the water up to a two storey house. However, the absolute minimum required head at the stop tap would be the head that is sufficient to raise the water up to the OHT.

In order to supply water to a secondary network, the primary node supplying the secondary network should have adequate pressure. The minimum required head can be derived from the minimum heads at the households. That is the minimum head that required to supply the secondary network (i.e. primary node head) is the minimum required head at the consumers stop tap and the lowest head loss provided by the route from a household to the primary node. Which is given by:

$$H_{PN} = H_S + HL_{Min} \qquad (4.47)$$

Where H_{PN} is the head at primary node, H_S is the head at the stop tap, HL_{Min} is the head loss along the path from primary node to a stop tap in a secondary network which gives the lowest head loss.

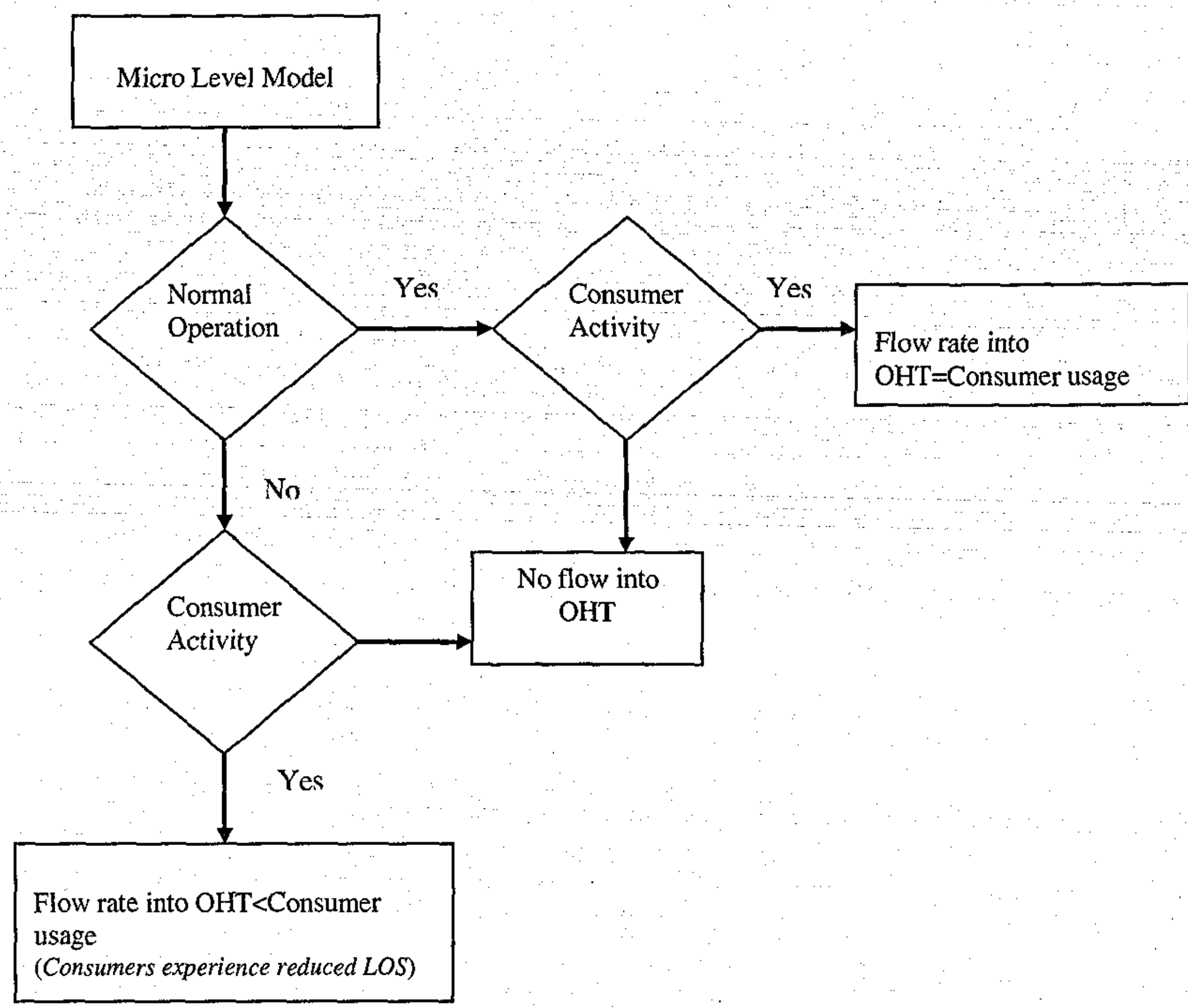


Figure 4.18: Flowchart indicating the Pressure Dependent Flow in MLM

The main purpose of the MLM is to simulate the behaviour of the PDD functions. This is achieved by having micro level models attached to each primary node of the WDS as shown in Figure 4.8. In the event of larger networks, incorporating complicated micro level models will be unrealistic. Therefore, micro level models can be further simplified using lumping methods described above. Once the WDS with micro level models is developed, it can be simulated for different scenarios.

4.6 Comparison of Analysis Methods

In the above sections, uses and issues related to the pressure dependent demand function, micro level models and also the conventional demand driven methods were discussed. However, in this section the three different approaches have been compared using a 30 node network given in Chapter 2. It was mentioned earlier that during normal operation of the WDS, both the demand driven and the pressure dependent systems operate similarly. The pressure dependent approach is only required to analyse extreme situations. Therefore, in the analysis below, performance of pressure dependent function is compared with other methods only during extreme situations (or failure events).

The MLM is compared with conventional demand driven method and the pressure dependent function proposed by Tabesh *et al.* (2002) (based on Wagner *et al.*, 1988b method). Unlike in Wagner's method, here the function is incorporated with the network analysis to account the flow redistributions in the network. Tabesh *et al.* (2002) method was specially selected due to the simplicity and ease of use and also it is recommended that this function is capable of accurately predicting pressure dependent demand.

When using Tabesh *et al.* (2002) pressure dependent demand function, the desired head and minimum head at nodes need to be specified. Here the desired pressure of 30m and a minimum pressure of 15m were considered. In addition, the exponent of the relationship is taken to be 0.5 which is generally used in the literature (Tabesh *et al.*, 2002).

Initially DD analysis method is compared with MLM during normal operation. A failure event is introduced afterwards to simulate the deficient network conditions by introducing a pipe burst at pipe 23. The network was analysed using all three (DD, MLM and PDD function) methods to compare the performances of WDS. During Normal operation of the network the pressures and flows at selected nodes are given in Figures 4.18- 4.21 below.

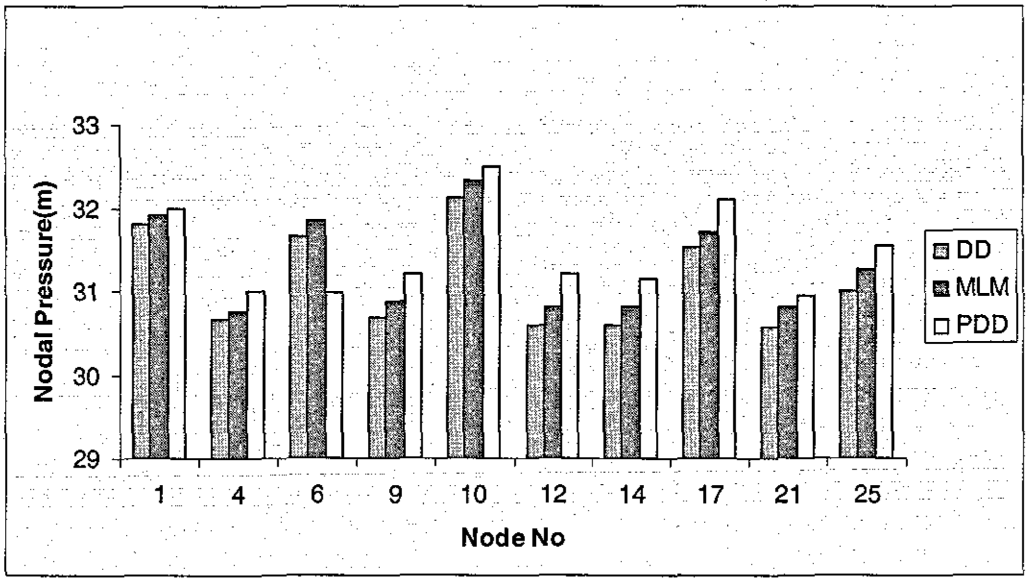


Figure 4.19: Head at selected nodes (normal operations)

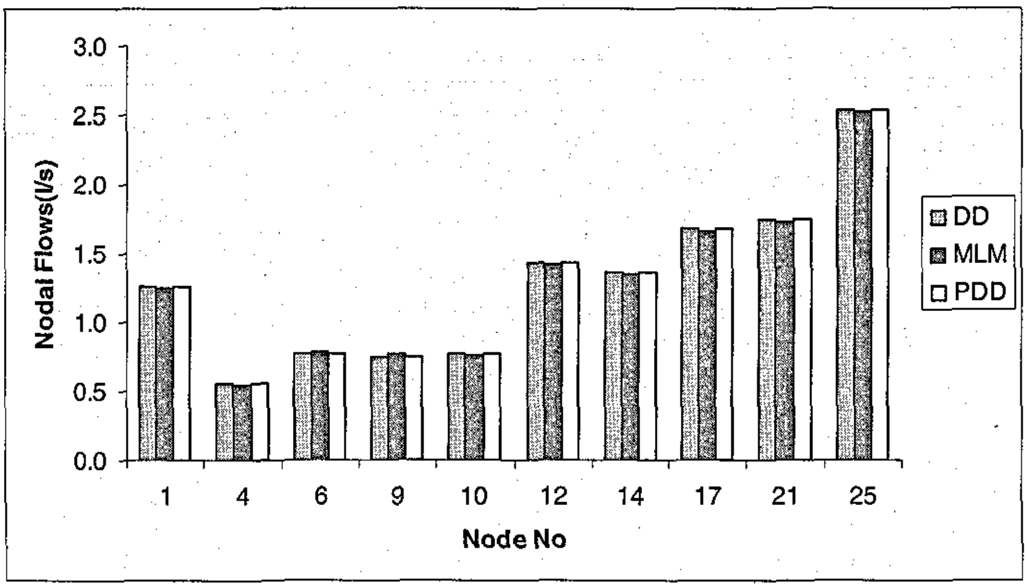


Figure 4.20: Nodal outflows at selected nodes (normal operations)

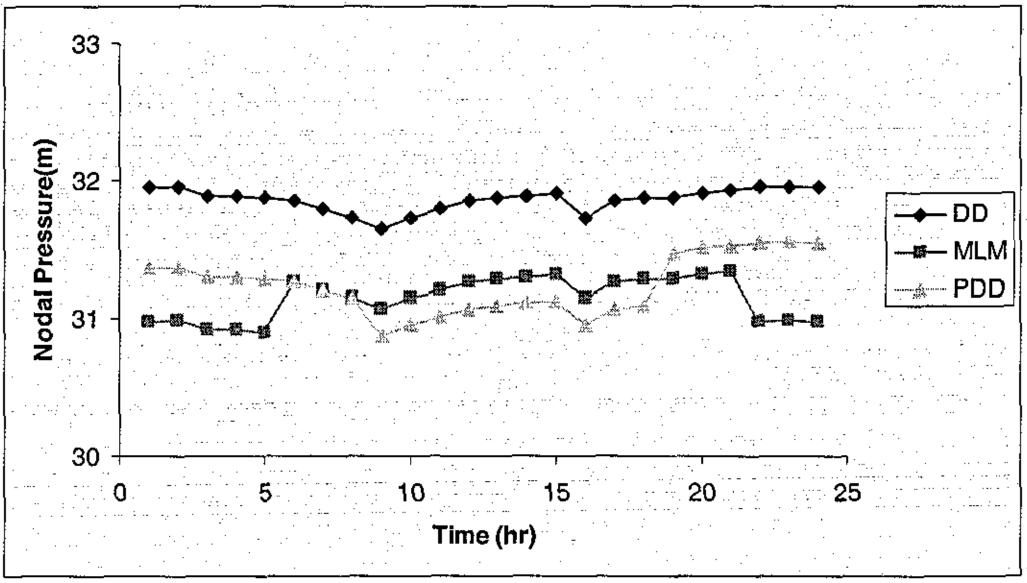


Figure 4.21: Variation in nodal Pressure for node 8 (normal operations)

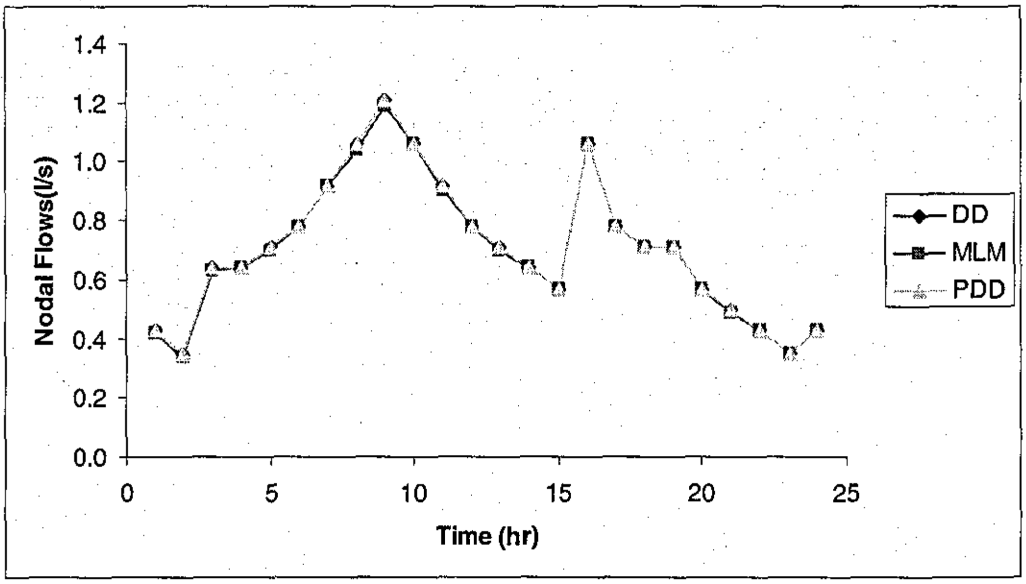


Figure 4.22: Variation in nodal outflows at node 8 (normal operations)

From Figures (4.19- 4.21) shown above, it can be seen that the variations in nodal pressure and that of flows are very small during normal operation. They fall below 5% on average, confirming that the PDD method, micro level analysis and the demand driven analysis give similar results during normal operations.

The next step is to demonstrate the difference in the results of DD and PDD analysis when applied to a failure. In this example a simple pipe burst is simulated in pipe 23 (between nodes 18 & 20). Clearly the consequence of this failure is a sudden drop in pressure and the redistribution of flows. It is unlikely that the DD model will be able to respond appropriately as it will continue to show demand being satisfied irrespective of the drop in pressure. However, it is expected that PDD analysis would show variations in demand due to the sudden drop in pressure.

Figures 4.22-4.25 show the outflows and pressures at selected nodes during the simulated failure event. From these figures it is clear that when the failure is simulated using DD analysis the pressures have dropped but the demand has not been affected (as it would be expected with a DD analysis). In some parts the pressures have fallen drastically (node 12) but still the nodal demands are being satisfied. Clearly this is a much distorted picture of what would happen in the network.

However, when the same failure event was simulated using the PDD (MLM and the PDD function) analysis, the picture is very different. Figures 4.22-4.25, indicate that there would be drop in pressure but this drop results in many nodes not receiving the desired amount of water (nodes in a failed mode).

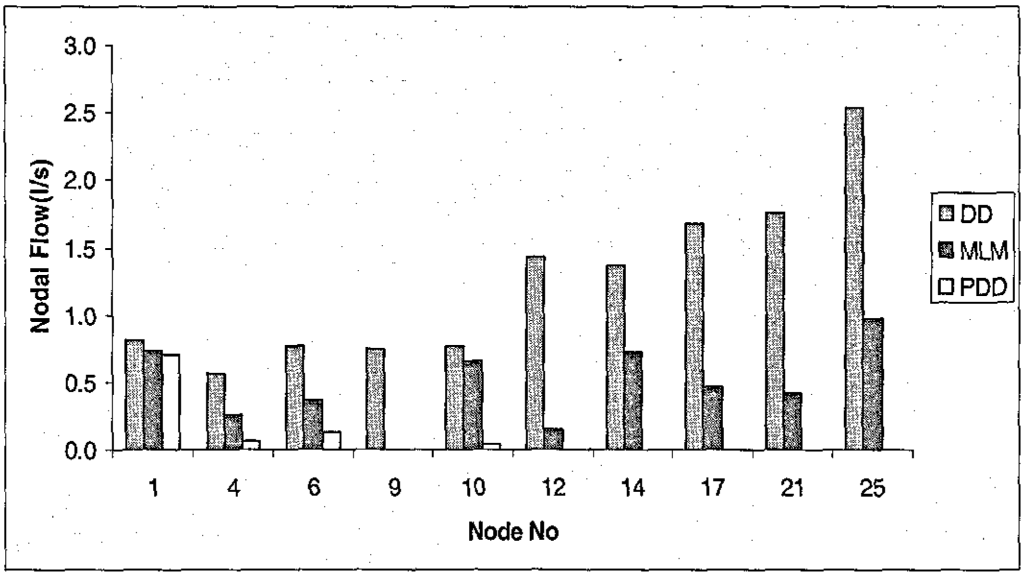


Figure 4.23: Nodal flows at selected nodes at 9 AM (failure)

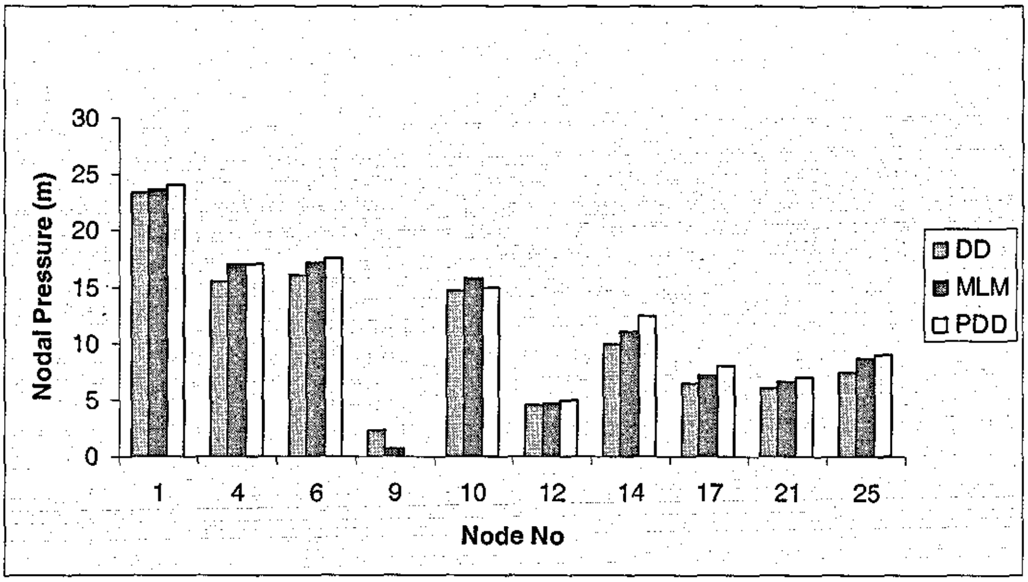


Figure 4.24: Pressure at selected nodes at 9AM (failure)

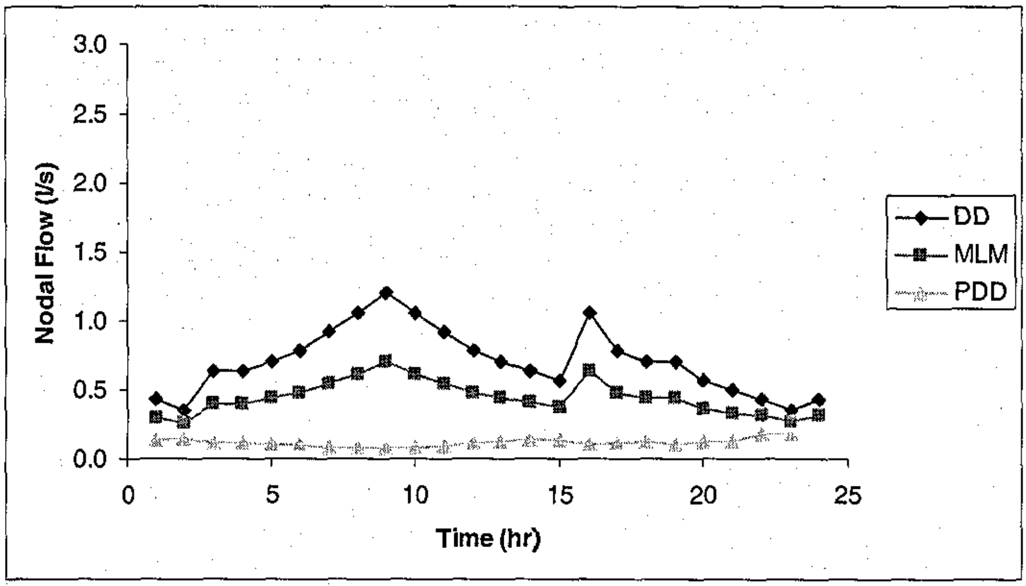


Figure 4.25: Variation in nodal outflows at node 8 (failure)

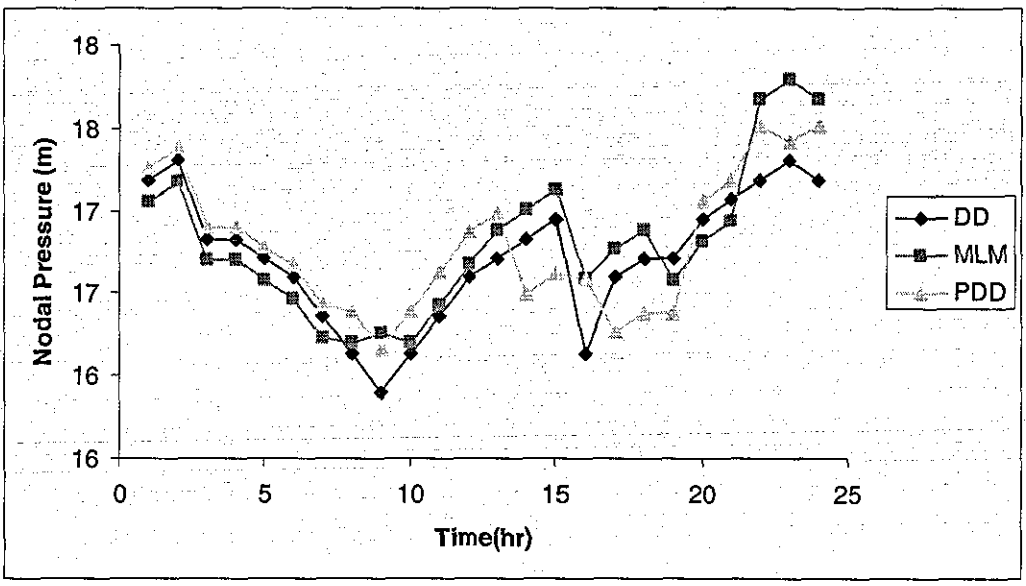


Figure 4.26: Variation in nodal Pressure for node 8 (failure)

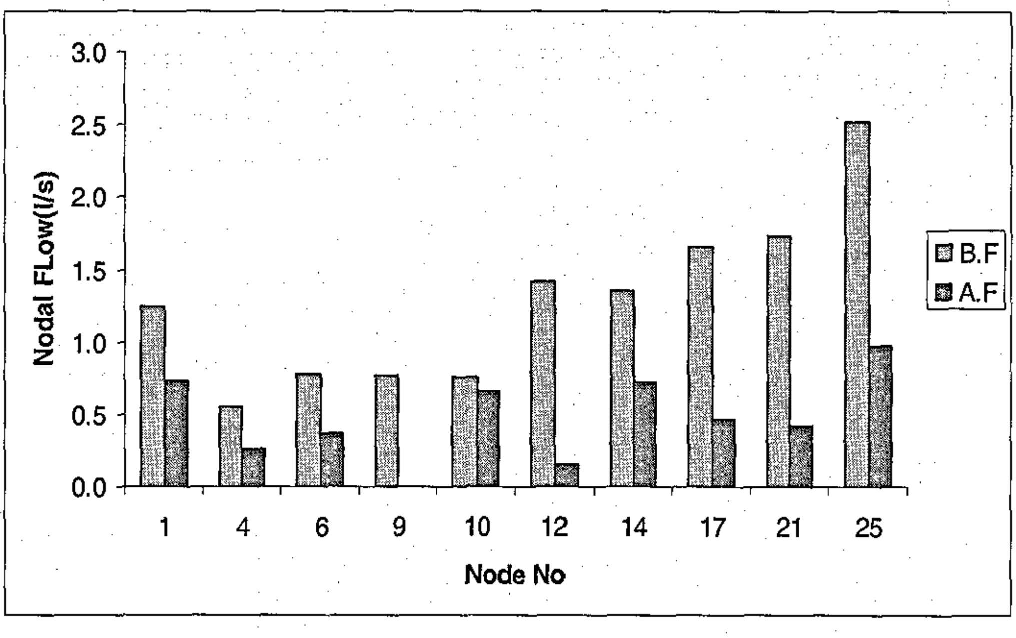


Figure 4.27: Nodal flows before and after the failure event at 9AM (from MLM method)

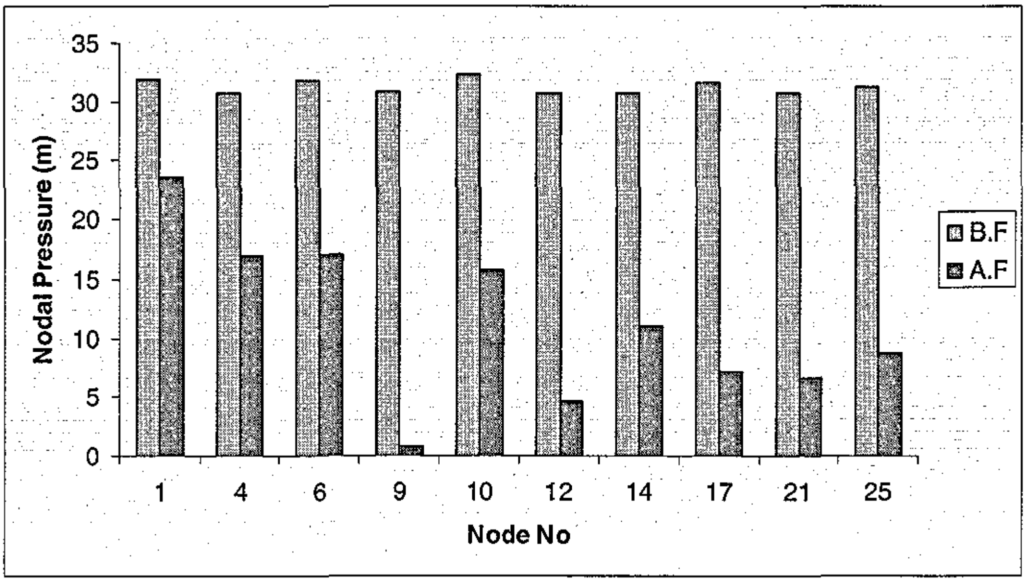


Figure 4.28: Nodal Pressure before and after the failure event at 9AM (from MLM method)

Key:
B.F: Before Failure
A.F: After Failure

Figures 4.22-4.25 illustrates the difference in the results of DD and pressure dependent analysis. During the extreme event DD analysis shows that the nodal demands are satisfied even though the network experiences pressure deficiencies. However, both pressure dependent methods (MLM and Tabesh's PDD function) show a drop in nodal demand corresponding to the pressure drops at nodes.

Analysis of the Figures 4.22, 4.23 and 4.24 indicate that certain nodes (9, 12, 17 &21) show zero flow for PDD function, but give a positive value for MLM analysis. This phenomenon is due to the fact that Tabesh's PDD function is not sensitive to the values outside of desired and minimum heads (in this case 15m) at the nodes. However, the MLM on the other hand predicts the pressure dependent demand outflows taking system characteristics into account. In other words the carrying capacities of each and every component (up to the households) are considered. From the above analysis it is evident that both PDD function and the MLM are sensitive to the pressure deficiencies in the system. However, there is considerable difference in prediction capabilities. Figures 4.26 and 4.27 shows the predicted flow and pressures before and after the failure event respectively. This indicate the sudden variation in the flow just after the failure event when the system is analysed using an appropriate pressure dependent analysis method (MLM). The arguments given above indicate the capabilities of MLM in predicting pressure dependent demands in WDS.

Therefore, Micro level models are more appropriate in predicting the nodal outflows during extreme events. However, when applying this method to large distribution systems, there will be complications as the size of the network increase exponentially due to the inclusion of the secondary networks. Therefore, in this thesis a new method is proposed to simulate the behaviour of secondary networks using artificial neural networks. This method eliminates the complications involved with the dimensions of the network.

4.7 Conclusion

In this chapter the network analysis techniques that are applied to deficient WDS are described and an alternative method to PDD functions introduced that incorporate the micro level models of individual nodes.

This chapter demonstrates the importance of the pressure dependent demand analysis in analyzing deficient water networks. The existing PDD analysis methods and their limitations were comprehensively reviewed. It was shown that they do not always predict the actual nodal outflows. An alternative method of analysis i.e. the micro level analysis method is introduced. This method is capable of representing the actual conditions in the WDS as they incorporate micro (secondary network) level details of the network.

Detail description of micro level (secondary) network development is presented and the applicability of MLMs to analyse pressure dependent nodal outflows in water distributions systems is demonstrated.

It was demonstrated that for pressure deficient conditions conventional demand driven method is not appropriate to analyse pressure dependent nodal demands. However, MLM and PDD functions were shown to be sensitive to pressure variations in the WDS. The PDD function was sensitive only within the range of minimum pressure and desired pressure for corresponding nodes. On the other hand MLM did not depend on the pressure ranges. Therefore, MLM method is more appropriate to analyse pressure deficient water distribution networks.

However, there are short comings involved in developing micro level models. Especially when there are large networks involved. The issue of applying MLMs to large size networks is dealt with by introducing artificial neural networks. The use of ANNs becomes essential to simplify the network model rather than having secondary networks at each and every node, therefore each secondary network is replaced by an ANN. This method is given in Chapter 5.

The principal conclusions of this chapter are:

- Demand driven method of analysis is not appropriate for pressure deficient WDS.
- PDD functions have limitations associated with them in terms of obtaining coefficients for individual nodes.
- PDD functions are sensitive to pressure variations in the WDS but their applicability is constrained by minimum and desired pressure ranges at the WDS nodes.
- Alternative PDD approach based on micro level analysis is more appropriate to analyse pressure deficient WDS.
- Applicability of MLM becomes complicated when applying to large WDS.
- Hence a method to apply MLM to larger WDS needs to be developed.

CHAPTER 5

ARTIFICIAL NEURAL NETWORKS IN PRESSURE DEPENDENT DEMAND ANALYSIS

5.1 Introduction

Understanding the water distribution network behaviour during pressure deficient conditions is the main component of the performance assessment of WDS. So far different versions of network analysis techniques which are dedicated to analysing the pressure dependent demand in WDS have been analysed. It is important to recognise that the nodal outflows are dictated by the secondary network characteristics as well as the piping arrangements of the consumers. One of the methods to incorporate the actual behaviour of the consumer is to incorporate secondary networks. Although this approach is the most intuitive and straightforward method, it has shortcomings in terms of practicality. Therefore, artificial neural networks that are able to simulate individual secondary network behaviour are considered.

In this chapter a new methodology based on Artificial Neural Network (ANN) to predict pressure dependent nodal outflows of WDS is proposed. The ANN is trained with the behaviour of the secondary network models and incorporated with the network analysis program to predict the pressure dependent outflows. In this way the secondary network behaviour is incorporated without physically incorporating the secondary network with the network analysis. As a result the actual situations in the WDS are represented during the network analysis.

ANNs are trained to mimic the behaviour of secondary networks by incorporating the secondary network characteristics. Each secondary network is represented by a set of parameters and ANN is trained using inputs and outputs from the secondary networks.

This chapter begins with a brief introduction to ANN and describes different types of ANN architectures. This chapter further presents the application of ANN in general, followed by applications to WDS. Based on behaviour of ANN and its application, the utility of modelling PDD functions of secondary networks and primary nodes is described. Finally presentation of ANN model developed in this study for predicting PDD function and its integration with the network analysis is described and demonstrated by applying it to a given network. The simulation results during normal operation and during failures are analysed using both the proposed method and the MLM described in chapter 4.

5.2 Artificial Neural Networks

Artificial neural network is inspired by the functioning of biological nervous system. ANNs are massively parallel distributed processing system. They consist of simple processing units (called neurons), that have a natural propensity to store and use experimental knowledge. ANN resembles the brain in that knowledge is acquired from its environment through the process of learning. Inter neuron connection strengths (synaptic weights) are used to store the acquired knowledge. Learning occurs through exposure (training) to a set of input/ output data where the training algorithm adjusts the weights iteratively. One of the most commonly used ANN is the feed forward Multi Layer Perceptron (MLP) coupled with back propagation training algorithm (Vemuri and Rogers, 1994).

The evolution of the field of neural networks has been going on for the past four decades. However, only in the last twenty years application of ANNs started to dominate in the fields of engineering and communication (Swingler, 1996). ANN is distinctly different from the fields of control systems or optimization where the terminology, basic mathematics, and design procedures have been firmly established and applied for many years.

Generally ANNs are trained such that particular input leads to a specific target output. In many cases, the network is adjusted (or trained) based on the comparison of the output with the target until the difference between the output and the target is a minimum.

Application of ANNs is particularly useful for the problems which are difficult to solve using conventional physical methods. They allow to model complex functions with non linearity built into them. This is possible only due to the ability of the ANN to learn the relationship of a particular problem by example and very little user domain expertise is required. It is important to note that ANNs cannot do anything that cannot be done using traditional methods, but they are capable of modelling complicated relationships, which would otherwise be very difficult to deal with.

General advantages of using ANNs include adaptation to unknown situations, fault tolerance due to network redundancy and autonomous learning and generalisation. ANNs are not exact as their size is variable and also the network may have large and complex structure, which again may influence the performance and accuracy of the model.

ANN is related to non linear regression in that they are able to build a non linear relationship of the problem concerned, but unlike the regression ANNs are much more flexible. They use training data to build the relationship by adjusting the weights. Furthermore, the relationship developed by the ANN is sensitive to the input parameters. The more sensitive the input parameter to the problem, the more accurate is the relationship built by the ANN. Therefore, to have better use of ANN models, it is essential to have the knowledge of the physical models.

More recently Support Vector Machines (SVM) have been introduced which are comparable to ANNs (Vojinovic and Kecman, 2004). In general SVMs are very similar to ANNs in their representational capacity however, main difference between the two models is found in the training process. Learning in SVMs are performed by solving a quadratic programming problem with linear equality and inequality constraints, whereas in ANN the learning is through solving a non convex, unconstrained minimisation problem (Osuna *et al.,* 1997).

Although SVMs are reported to have better performances in certain instances (Han and Cluckie, 2004), most of the success stories of SVMs are found in the field of pattern recognition and optical character recognition (OCR). The application of SVM in time series and regression are still at early stage and are much more problematic compared to classification problems (Sivapragasam *et al.,* 2001; Han and Cluckie, 2004)

ANNs are the popular choice for forecasting and prediction in hydraulic studies (Solomatine and Price, 2004). It is a very successful method in modelling non linear relationships. However, there are limitations associated with ANNs when applying to these models:

- They require large amount of data to train the model to develop a relationship between inputs and outputs.
- They are trained as global models to represent the whole data set (resulting models are not transparent).

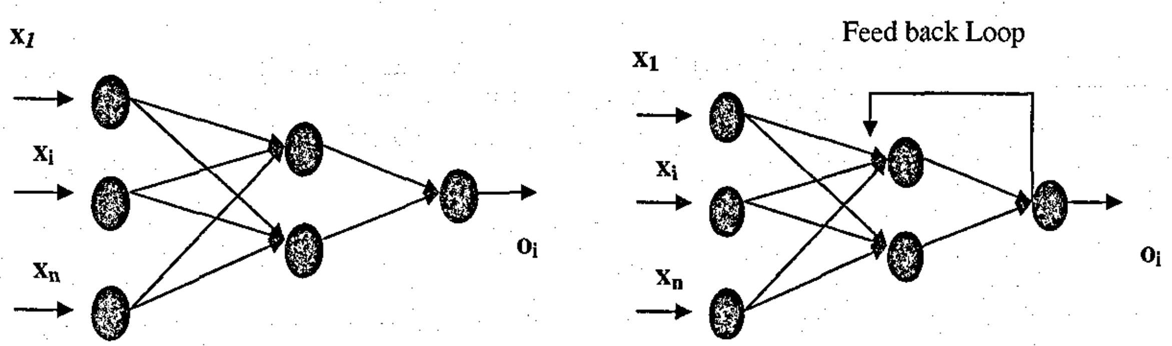
The data requirement is inevitable as ANNs are primarily data driven models, however input parameters for training can be intelligently selected to minimise the amount of data required for training.

The relationships developed by the ANNs are not transparent because unlike in the physical models they learn the relationship between the data sets therefore, the accuracy of the model depends on the accuracy of the data sets. Solomatine and Price (2004) proposed an alternative to building global models with ANNs by suggesting the building of a number of simpler local models for various regions of input space. This gives the opportunity to develop less complicated models with higher accuracy in prediction.

5.2.1 Types of Artificial Neural Networks Architectures

Artificial Neural Networks are classified based on their characteristics and architecture. ANNs are mainly categorised into two groups based on their architecture.

- Feed forward neural networks.
- Feed back neural networks.



Feed Forward Network Feed Back Network

Figure 5.1: ANN architectures

Where

$\mathbf{x}=[x_1,x_2,..x_i..x_n]$-input vector and $\mathbf{o}$- is the output vector in the ANN.

Feed forward networks are the ones which allow the information flow only in one direction that is from input to output. There is no feed back loops, in other words outputs of any layer does not affect the same layer. These networks are straight forward since they directly associate inputs to the outputs. This type of organisation is called the bottom up approach. Some of the feed forward architectures include multi layer perceptrons and radial basis functions.

Feed back networks are ones that can have information travelling in both directions. This is achieved by introducing a feed back loop in the network. These networks are very powerful and often get extremely complicated. Feedback networks are dynamic, their state changes continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes. Feedback architectures are also referred to as interactive or recurrent networks. Examples of feed back architecture include recurrent networks, time delay networks and Hopfield networks. Figure 5.1 shows the structures of feed forward and feed back networks.

This chapter mainly covers multi layer percptron networks as they are the architecture employed in this study. Other types of networks also have been briefly discussed. Comprehensive reviews of these can be found in standard text books on artificial neural networks (Bishop, 1995).

5.2.1.1 Multi layer perceptron networks

Multi layer perceptrons (MLP) are the most widely used ANNs (Swingler, 1996 and Bishop, 1995). This falls under the feed forward architecture. Perceptron is a hypothetical nervous system designed to illustrate some fundamental properties of intelligent systems (Cerda-Villafana *et al.*, 2004; Khanna, 1989). A MLP has a set of input values, obtained from outside, a set of output units to predict the final answer, and a set of processing (hidden) units which links the inputs and the outputs. The network is arranged into layers of units with differentiable activation functions (linear, sigmoid, hyperbolic tangent etc.) and the value displayed by each unit is known as its activation and measures the degree to which it affects higher units. A typical MLP is shown in Figure 5.2.

Feed forward multilayer networks are architectures, where the neurons are assembled into layers and the connection between the layers go only in one direction, from the input layer to the output layer. There are no connections between the neurons in the same layer. However, there may be one or several hidden layers between the input and the output layer.

These architectures are static (not time dependent), so the mapping between the input and the output is a static function. In practice, this also means that the network does not have memory, where it could store contextual information from the past. Therefore, the input of the network must contain all the necessary contextual information which is used in representing the output.

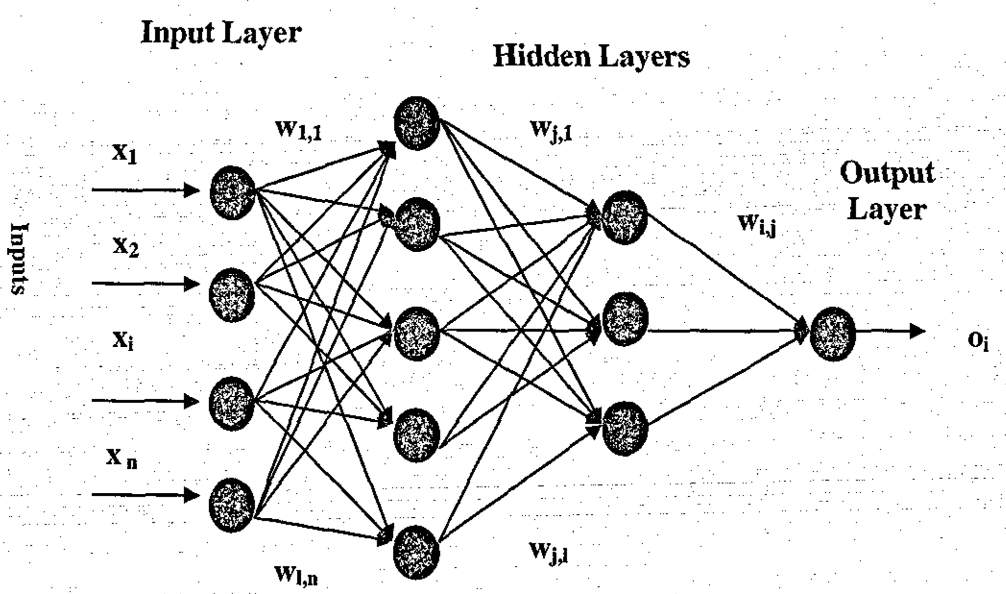


Figure 5.2: Multi layer perceptron

Where x= $[x_1,x_2,x_3,.....x_n]^T$ are the inputs to the network, $w_{l,n}$ is the weight from the input n^{th} unit to the l^{th} hidden unit, $w_{j,l}$ is the weight from l^{th} hidden unit to j^{th} hidden unit, $w_{i,j}$ is the weight from j^{th} hidden unit to the i^{th} input unit, o_i -is the i^{th} output unit.

The MLP is a nonlinear model consisting of number of neurons (units) organized into multiple layers, forming a mapping $o = f(x,w)$ between the input x and the output o, adjusted by the weights w. This mapping with certain architecture and weights forms a static, nonlinear function. The complexity of the MLP network can be changed from an almost linear model to a highly nonlinear model by varying the number of layers, the number of units in each layer, and the values of the weights. A typical single hidden layer MLP network architecture with i outputs gives rise to the $f_i(x,w), i = 1,..., I$ with weights w. The model has the functional form:

$$f_i(x,w) = \sum_{j=1}^{q} w_{ij} g\left(\sum_{i=1}^{n} w_{jn} x_i\right) \qquad (5.1)$$

Where n number of inputs, q is the number of hidden layer units, g is the activation function for the hidden layer units and indices j and i correspond to the output and the hidden units respectively, w_{ij} and w_{jn} are the weights from hidden unit j to the output unit i, and from input unit n to the hidden unit j. I, the number of output units.

A practical problem with neural networks is the selection of the correct complexity of the model, i.e., the correct number of hidden units or correct regularization parameters. It is well known that plain optimization of the MLP may lead to severe over fitting of the relationship modelled by the ANN. The searches for the optimal parameter values which maximize the respective learning algorithms search to minimise the error metric for the given data. Usually, the model that gives the smallest error for the training data does not generalize well with the new data. This is because the model starts to represent the noise in the training data. The MLP is a quite flexible model, and efficient learning algorithms are applied in searching the optimal parameter values. Regularization methods are needed in order to provide good generalization ability. Traditionally, complexity of the MLP has been controlled with early stopping or weight decay methods (Bishop, 1995).

5.2.1.2 Radial basis networks

Another feed forward architecture is radial basis function (RBF) network. This consists of two layers; a hidden radial basis layer and a linear output layer. RBF network training is said to be substantially faster than the methods used in MLP training due to the two stage training process of the network. In the first stage the parameters governing the basis function (corresponding to the hidden units) are determined by (relatively fast) unsupervised methods (only input data is used, not target data). The second stage involves the determination of the final weights obtained from solving a linear problem, which is therefore fast. However, the shortcoming of the RBF function is that it consumes a considerable amount of memory when generating the network, it also would need as many hidden neurons as there are input vectors (Bishop, 1995; Swingler, 1996).

Radial basis functions (RBF) are ones whose activation of a hidden unit is determined by the distance between the input and target vectors. These functions have wide applications in function approximation, regularisation, noisy interpolation, density estimation, optimal classification theory and potential functions (Bishop, 1995). A typical RBF network is shown in Figure 5.3 below.

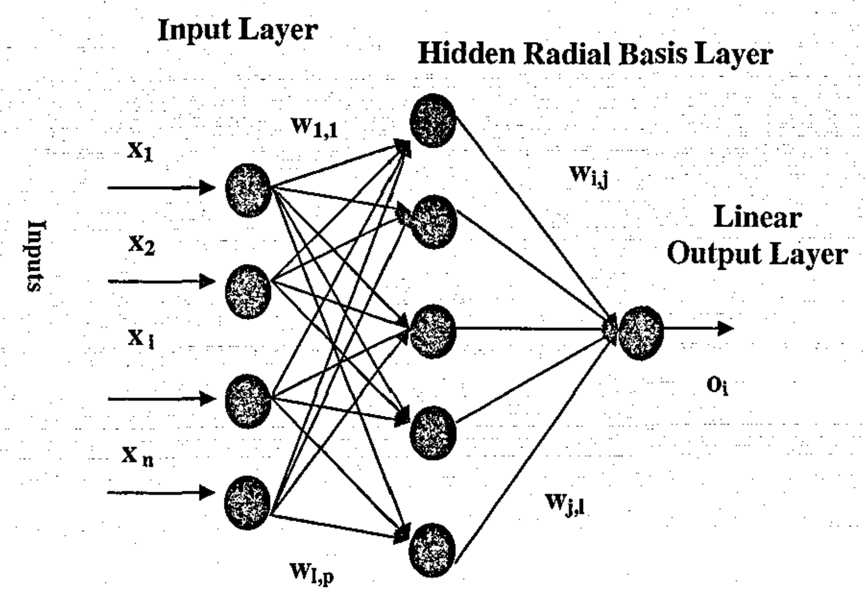


Figure 5.3: Structure of a RBF network

5.2.1.3 Time delay networks

Dealing with time varying data introduces new complexities to the modelling of the systems. Time varying systems can be predicted in two ways:

- By using the MLP networks.
- By using Time Delay Networks (TDN).

The main difference between modelling time varying data using MLP and TDN is that in MLP, the time varying data is presented to the network as ordinary inputs and in TDN the current value of the time varying output is predicted from inputs of previous time step.

The characteristic of the time delay systems is that one has to remember the things that happened before and wait for those yet to happen (Swingler, 1996). One way of resolving this is by developing a memory and a method to encode it in order that it interacts with new information as it is received. However, this method is not the most efficient way of dealing with time varying data. For example in sound recognition the brain doesn't have to remember the whole stream of air pressure values (Swingler, 1996). A typical Time Delay Network is shown in Figure 5.4 below.

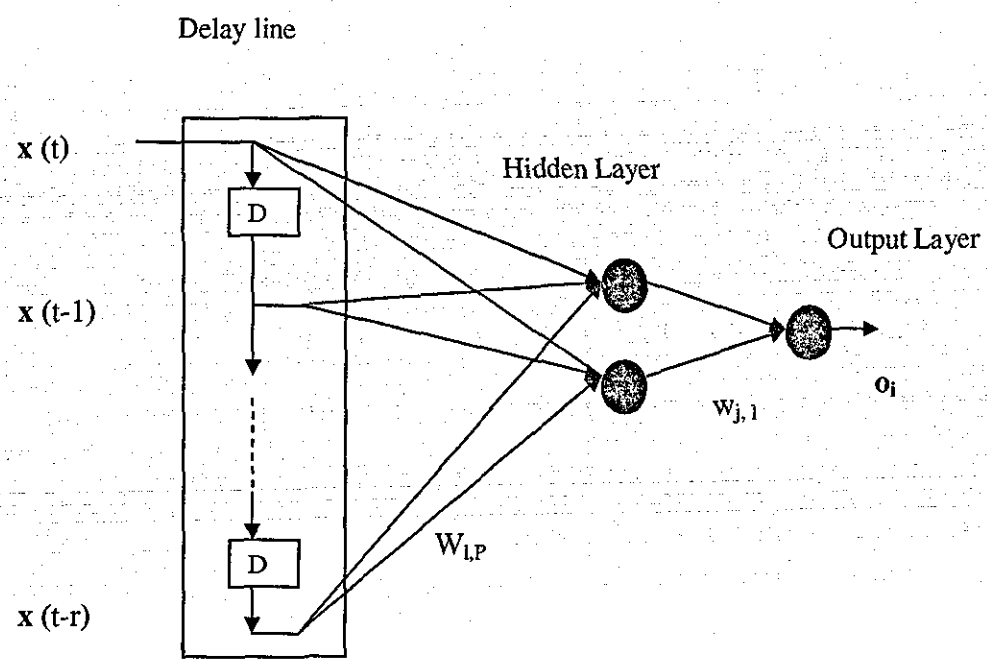


Figure 5.4: Typical Time Delay Neural Network

Where D represents delay between successive time intervals, t is time and r is number of delays. Other notations are same as before.

In the TDN, the network has an input layer, and one or several hidden layers. The number of neurons used may vary. The input of the network is fed to the delay line. Values stored in the delay line are then fully connected to the hidden layer neurons, thus the input layer implements the delay coordinate embedding the time series. The difference between TDN and MLP comes from the hidden layer. In the TDN, the previous outputs of the hidden layer units are stored in delay lines. These values are then fully connected to the output layer (in univariate case output neuron), which combines all values together.

5.2.1.4 Recurrent networks

Another network which can be used with time dependent data is the recurrent networks. These are feedback networks. Recurrent networks are capable of building their own time lag (Swingler, 1996). Elman (1991) demonstrated the ability of recurrent networks in learning the temporal dependencies in grammatical sentences. Lin (1992) illustrated that recurrent networks used for reinforcement learning had the advantage of being able to use the features in the systems history. Figure 5.5 illustrates a Recurrent Neural Network.

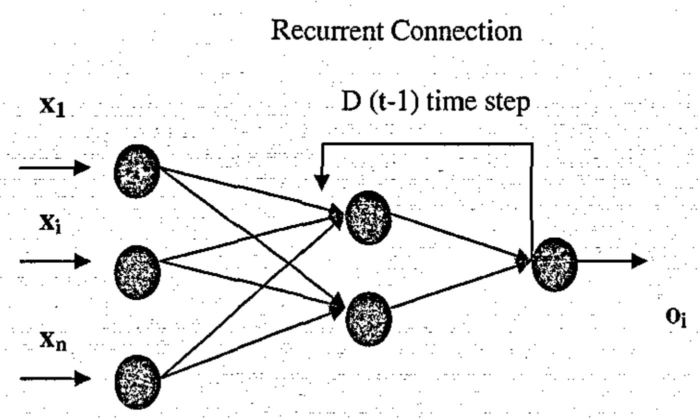


Figure 5.5: Structure of a Recurrent Neural Network

Recurrent networks are unsuitable for tasks which include non temporal data. The entire input layer is referred to, when the context layer is built; it is not possible to include static variables without them being treated as part of a time series. Incorporating everything as part of the system history introduces extra complexity; however, this limitation can be overcome by splitting the hidden layer into two: one for temporal variables and the second one for independent variables. Hence only the values in the temporal part of the hidden layer would be fed back into the recurrent context buffer leaving the effect on non temporal data limited to the time step at which they are received (Swingler, 1996).

5.2.2 Training the ANN

The most important aspect of using ANN is training the network to obtain a relationship by way of providing the network with examples (data). Therefore, it is of primary importance to obtain data which contribute to the behaviour of the relationship concerned. It is helpful to have an understanding of the physical model that depicts the relationship in order to select appropriate parameters for the data set.

The data set should be of sufficient size and also include wide ranging different conditions so that the ANN will be able to learn the entire characteristics of the relationship. Once appropriate data set is selected, the all important training process can be started.

This section is only concerned with the training of the MLP. Training the ANN is the next important activity after deciding the architecture. It is generally carried out in one of two methods.

- Sequential training.
- Batch training.

In sequential training the weights and the biases of the networks are updated each time when an input is presented to the network. The sequential training mode can be applied to both dynamic (time dependent) and static networks (Bishop, 1995). The training data can be presented sequentially (as with dynamic networks) or concurrently.

On the other hand, in batch training the weights and the biases are only updated after all the inputs have been presented. Batch training method can also be applied to both static and dynamic networks. During training the input vectors can be placed either in a matrix of concurrent vectors or in a cell array of sequential vectors. But for dynamic networks, the input vectors need to be passed as concurrent vectors. Generally batch training requires less weight updates hence, it is faster and also provides more accurate measurement of the required weight changes. However, it is more likely to become trapped in a local minimum in the error space (Swingler, 1996)

Training is a procedure for modifying the weights and the biases of a network. This is applied to make the network learn to perform particular tasks. Learning can be generally categorised into two as; supervised learning and unsupervised learning.

In supervised learning, the ANN is provided with examples of the behaviour of the network (training set). As inputs are applied to the network, the network outputs are compared to the targets from the training data set. The weights and biases of the network are adjusted in order to move the network closer to the target.

In unsupervised training, the weights and the biases are modified only in response to network inputs. There are no target outputs to compare the network outputs. These algorithms are used to perform clustering operations. They are capable of categorising the input patterns into a finite number of classes. Unsupervised learning is especially used in vector quantization (Swingler, 1993, Khanna, 1989).

In this research we are only concerned with the supervised training methods, as pressure dependent demand outflows of WDS are predicted using MLPs. When training the MLPs the standard training algorithm used is based on back propagation of error (Bishop, 1995). Comprehensive reviews of the back propagation training algorithms can be found in Bishop, 1995 and Swingler, 1996.

5.2.3 Testing and Cross validation

One of the problems that occur during the training process is the over fitting. The error on the training set is driven to a very small value, but when the data is presented to the network the error becomes large. In this instance, the network is said to have memorised the training example rather than learning it to generalise to new situations.

There are methods proposed to improve the network generalisation (Bishop, 1995). One of the methods includes using a network which is just large enough to provide an adequate fit. The larger the network used, the more complex the functions the network would generate.

The main problem in generalising a network is predicting the size of the network beforehand for a particular application. Some of the methods used to improve the generalisation of the networks are regularisation and early stopping.

5.2.3.1 Regularisation

Regularisation involves modifying the performance function, usually taken as the sum of squares of the network errors on the training set (*MSE*) as given in equation 5.5. This function is modified by adding a term consisting of the weights and biases which is shown below in equation 5.2.

$$MSE_{reg} = \gamma MSE + (1-\gamma)MSW \qquad (5.2)$$

Where γ is performance ratio, MSE is the mean square error of weights (performance function), $MSW = \frac{1}{m}\sum_{k=1}^{m}(w^k)^2$ and w^k is the weight vector at k^{th} iteration.

This modified performance function makes the network to have smaller weights and biases and forces the network to respond smoothly making it less likely to over fit.

5.2.3.2 Early stopping

The data set is divided into training data, validation data and testing data. Iterative learning algorithm gradually optimizes the network weights, until the error metric estimated from the validation data set starts to grow. The training is stopped before the minimum training error is reached, and the complexity of the model is regularized.

The training data set is used to compute the gradient and update the weights and biases of the network. The error on the validation set is continuously monitored during the training process. During the initial phase of the training both training error and validation error continue to decrease. However, when the network starts to over fit the data, validation error will start to increase, at this moment the training is stopped and the weights and biases for the least validation error are returned.

The error on the test data is not used during training but is used to compare different networks. If the error in the test set reaches minimum at a significantly different iteration number than the validation set error, this will indicate poor division of the data set.

5.3 Application of Artificial Neural Network

Artificial neural networks are a powerful tool that can be applied to problems which are highly complex and difficult to solve using physical methods. ANNs behave as a black box. The relationships and mathematics used is not explicit to the user. However, ANNs are applied in a wide variety of fields.

5.3.1 General Applications of Artificial Neural Networks

The versatility of the ANNs has paved the way for them to be used across a broad range of disciplines such as economics, engineering, communication, mathematics, science and military are a few but to mention. Most of the time ANNs are successfully used in applications like pattern recognition and speech recognition, due to the improvements in the development of ANNs. In this section application of ANN techniques in civil engineering, particularly in water sector is investigated.

Huang and Foo (2002) applied ANNs to predict salinity in rivers. A three layered MLP was used to predict the salinity variation in the Apalachicola River in Florida. The ANN was trained with the hourly salinity, the daily river flow and the hourly tidal data. They applied the trained model to an independent data set. They established that the ANN model was capable of correlating the non linear time series of salinity and the multiple forecasting signals of wind, tides and freshwater inputs in the Apalachicola River.

Abebe and Price (2004) employed MLPs to forecast surge prediction accuracy on the Dutch coast. They used data on wind speed, observed and predicted surge at selected locations, predicted wind and pressure fields, to train the ANN with the connection between the data and the surge prediction accuracy. They concluded that the ANN model was capable of forecasting the bias and the confidence interval of the surge prediction with remarkable accuracy.

Maier *et al.* (2004) applied ANNs to predict optimum alum doses and treated water quality parameters in Southern Australian surface waters. They used multi layer perceptrons to predict both water quality parameters and optimal alum doses. The inputs to the ANN model predicting the treated water quality were raw water quality parameters and applied alum dose. The inputs for optimal alum dose model were raw and treated water quality parameters. They stated the ANN models displayed good prediction capabilities.

Solomatine and Torres (1996) develop the neural network tool "NNN" based on feed forward multilayer perceptron to model the Apure river basin in Venezuela. They incorporated this ANN model with Mike-11 to optimise a system of three reservoirs. The ANN was trained with daily and weakly data with time spans ranging from 1 to 5 years and number of inputs ranging from 25-29.

Lee *et al.* (1999) used ANNs to develop software sensors to estimate nitrogen based oxides and ammonia in sequencing batch reactors. They used two separate models for anoxic and aerobic periods. This model was criticised due to its complex nature and the inability to modify the model (Kim *et al.*, 2004).

Similarly Anctil and Tape (2004) used multilayer ANN models to forecast rainfall run off. Almasri and Kaluarachchi (2004) employed modular neural networks to predict nitrate distribution in ground water. Also a number of ANN applications in water sector are available in refereed journals.

5.3.2 Application of ANNs in Water Distribution Systems

Even though, ANNs have found wide range of applications in many disciplines; there are only a handful of applications found in water distribution field. Still very few applications are found in replicating the behaviour of water distribution systems (Xu and Goulter, 1998).

Martinez *et al.* (2005) applied ANNs to simulate extended period simulation model of water distribution system. They generated input vectors for the ANN model from a calibrated hydraulic model of the water distribution system. The calibrated hydraulic model was fed with random data generated using the online SCADA measurements. This step was introduced to minimise the errors in the SCADA measurements. They used a single ANN to simulate the entire distribution system. Parameters used for the ANN training included 24 inputs (from 6 pumps, 10 regulating valves, 6 zone demands and two tank levels at time t) and the 18 output variables comprised of power consumption of 6 pump groups, 6 flows produced from plants, 4 pressures at critical nodes and 2 tank levels at time $t+1$. Several different architectures were considered and a three layer MLP with 24 input nodes, 100 hidden nodes and 18 output nodes was selected as the optimal architecture. Parallel computing facilities were used for the ANN training to reduce the duration of the training process. The results of the ANN model showed that the output variables can be predicted with an error less than 1.7%.

Freni *et al.* (2004) applied multilayer perceptrons to model the instantaneous residential water demand in a water distribution system. They obtained the optimal architecture of a MLP network by trial and error using various input data. A three layer network with 7 inputs, 42 hidden and 1 output unit was considered as the optimal architecture. They trained the ANN with measured data which consisted of water demand at previous time step (at time $(t-1)$), time, day ,month, pressure at the inlet node at the previous time step and daily maximum and minimum temperatures. The results of the ANN model was compared with the Poisson model (Buchberger and Wells, 1996) and found to be more accurate, less complicated and robust.

Skipworth *et al.* (1999) attempted to model water quality in distribution systems using ANNs. They tried to predict Oxidation Reduction Potential (ORP) at single and multiple points in the water distribution system. A multilayer perceptron network with two hidden layers of six and three nodes was used. Hydraulic and water quality data were measured downstream of the service reservoir that supplied the distribution system. Nine variables were used for the training of ANN which included the temperature at time t (T_t), the ORP at time t (ORP_t), and the flows at time t to t-6 ($Q_t, Q_{t-1}, \ldots, Q_{t-6}$). The output from the ANN was ORP_{t+3}. The input variables were selected depending on the sensitivity of the inputs to the output. Comparison of the predictions carried out using ANN model gave good indication that ANN models are a viable option to predict water quality in distribution systems.

Unlike the previous applications, the method presented in this chapter is developed to predict the pressure dependent nodal outflow in the water distribution systems. The main advantage of using this ANN based model is that it tries to mimic the actual behaviour of the micro level (secondary network) models. Detail illustration of application of ANN to simulate the micro level model behaviour is given in section 5.4.

5.4 ANN Model for Pressure Dependent Analysis

The method developed in this section is to use the ANN to predict pressure dependent outflows from water distribution systems. The ANN model applied in this section is based on the characteristics of the micro level models in the WDS. The main advantage of using the ANN based model is that it tries to mimic the actual behaviour of the micro level (secondary network) models. Detail illustration of application of ANN to simulate the micro level model behaviour is also given in this section. Figure 5.6 shows the basic concept of representing secondary networks using ANNs.

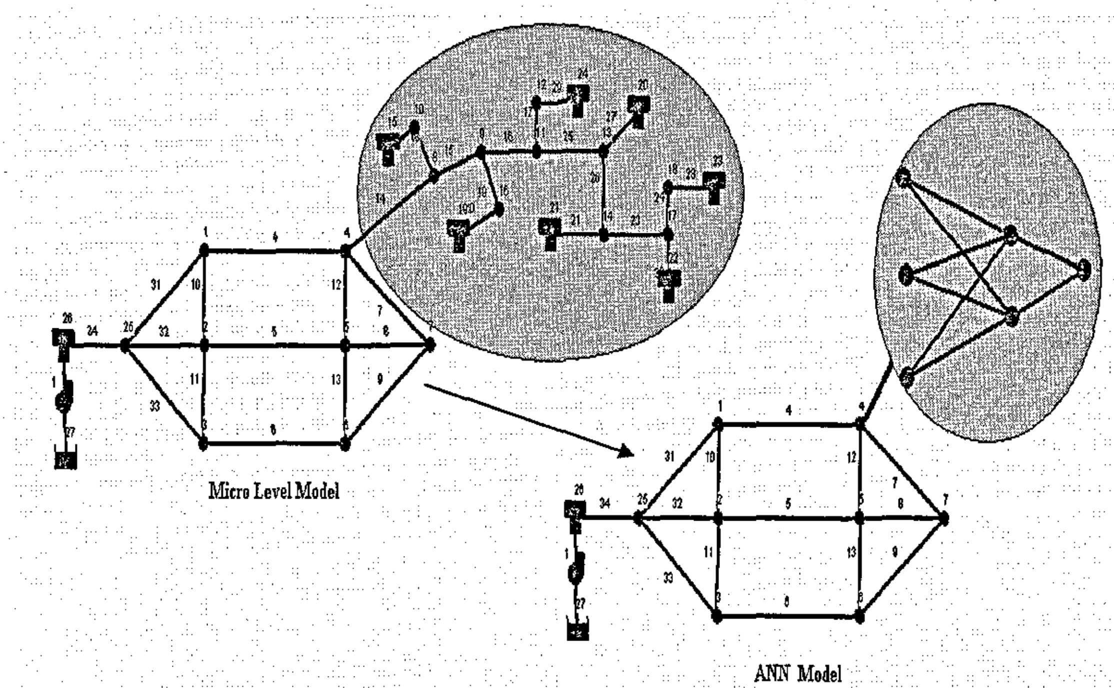


Figure 5.6: Secondary network and ANN Models (Not to scale)

The ANN method for pressure dependent analysis consists of following steps;

- Representing secondary networks using the ANN to simulate the pressure dependent demand.
- Integrating the ANN to network analysis.

This section describes the methodology.

5.4.1 ANN Model for Representing Secondary Networks

Pressure dependent demand in WDS can be simulated by incorporating secondary networks. This has been extensively explained in chapter 4. This indicates that secondary networks employ an implicit pressure dependent demand relationship. This unknown relationship varies node to node with the characteristics of the corresponding secondary networks which are attached to the primary node. Since pressure dependent demand relationship of secondary network cannot be physically represented a black box approach to model the relationship is needed, therefore the uses of ANN.

Artificial neural networks (ANN) are capable of modelling complex relationships using a combination of linear and non-linear functions. The PDD relationship in a WDS depends on the characteristics and behaviour of secondary networks. The unknown pressure dependent relationships that are implicit in the secondary networks can be trained using an ANN. This is achieved by training various characteristics of secondary networks of the water distribution system. The activities involved in training the artificial neural network with secondary network characteristics are listed below:

- Obtaining secondary networks of WDS.
- Obtaining data that represent secondary network characteristics.
- Obtaining optimal ANN architecture.
- Training, testing and validation.

5.4.1.1 Obtaining secondary networks

Secondary networks are the networks that are fed by primary nodes. These networks usually take after the road layout in the area. Consumers receive water through the service pipe which connects the secondary network and the households. Although in reality, secondary networks are looped networks, during the modelling and analysis, they are considered as tree shaped networks (Reddy, 1990). When converting the looped secondary network into a tree network, care should be taken so that the original characteristics (flows in the pipes) of the network are maintained.

A WDS has as many secondary networks as the number of nodes. Each primary node in the network is modelled as a secondary network. This process is easily done with the use of GIS. Individual secondary networks are modelled using EPANET network simulation software

(USEPA, 2000). The primary node corresponding to the each secondary network is represented by a constant head reservoir. The variation in the primary node head is represented using a pattern curve.

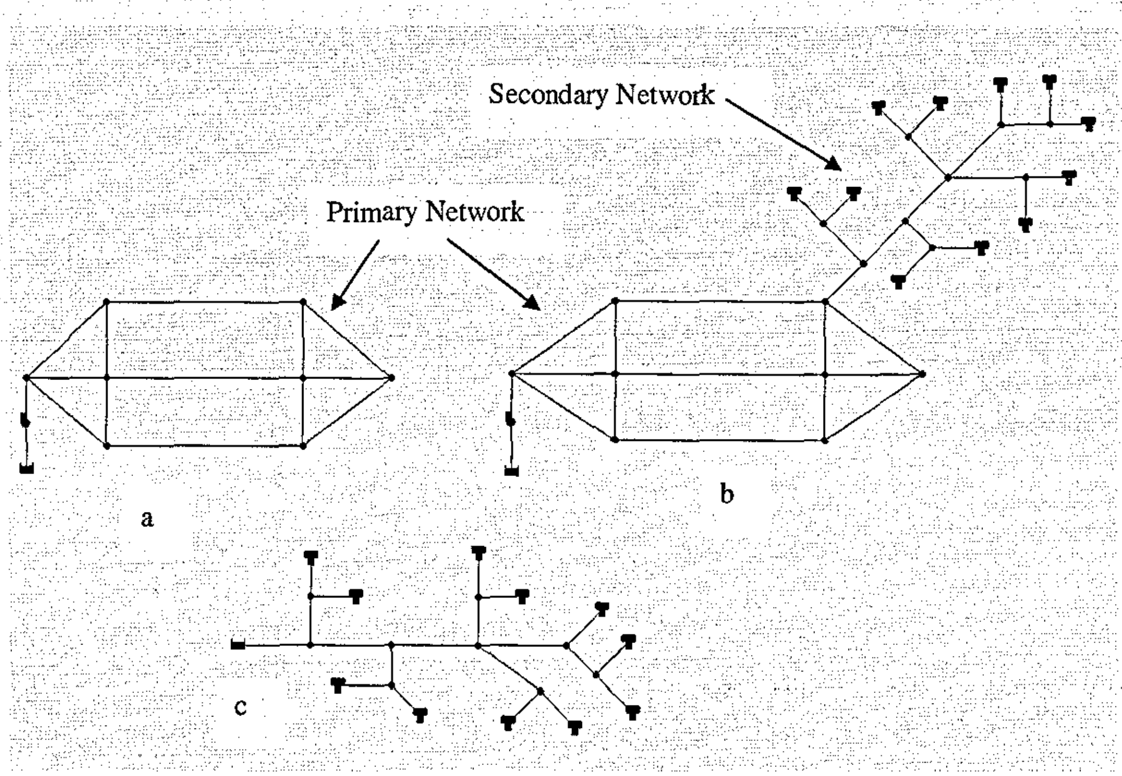


Figure 5.7: Secondary network models

Figure 5.7 a, b and c shows the primary network, secondary network which is fed from the primary node and the secondary network with primary node replaced by the constant head reservoir respectively.

5.4.1.2 Data representing secondary network behaviour

The behaviour of the WDS is mainly characterised by the physical characteristics of the water distribution system and the consumers' behaviour. WDS is a collection of secondary networks interconnected by a network of pipes. Demand in the distribution system is dictated by the consumers, whereas the flows in the pipes depend on the physical characteristics of the network itself.

Physical characteristics that contribute to the behaviour of the water distribution system include; the spread of the network, the size and the age of pipes (influence the carrying capacity of the

WDS). The larger the network size, the more completed it becomes. Pressure in the network is influenced by the size and the age of pipes. Larger diameter and newer pipes in the network will cause low head losses. On the other hand smaller and older pipes are one of the causes of pressure deficiencies in the distribution system. When considering the secondary networks in WDS, the size of the network and the diameters of the pipes will be much smaller. The variation in diameter in the secondary network will be much less compared to the variations in the primary network. Therefore, the secondary network behaviour is influenced by the physical characteristics such as length of pipes in the secondary networks and number of branches associated with the secondary network.

The length of pipe indicates the length of the largest pipe in the secondary network, which receives the supply from primary node. When comparing lengths of different secondary networks, the original pipes are converted to equivalent pipes with 100mm diameter with appropriate carrying capacity. This is done in order to maintain uniformity among the secondary networks.

Factors related to the consumer behaviour mainly impact the water network demand. The consumer demand in the water distribution system is proportional to number of consumers in the system, types of the consumers and consumer usage behaviour. These factors are the main contributors to the flow in the pipes. Hence, factors that contribute to the consumer demand can be represented by number of consumers and the average demand in the secondary network.

Therefore, parameters used to train the artificial neural networks with the behaviour of secondary networks are: length of pipes in the secondary networks, number of branches in each secondary network, number of consumers in a secondary network and average consumer demand in the secondary network area. These variables are unique to each secondary network. In addition to the above, the primary node head, the simulation time steps, head at the reservoir at a time step and the corresponding flows into the secondary network are additional information that is needed to train the ANN.

The simulation time step and the head at the reservoir are important to predict the flows during different time steps. These two parameters drive the extended period simulation in a network analysis.

The secondary node characteristics are obtained form the water network information and also from the ordinance survey maps. The primary node heads at different time steps are obtained from the simulation of the lumped micro level model. Flows in to secondary networks are obtained from simulating the secondary networks with the heads obtained from the lumped MLM. Table 5.1 below shows the table which is used in the arrangement of secondary network information to train ANNs.

Table 5.1: Data representing individual secondary networks

Secondary Network No:			
Average Demand (l/s): **No of Consumers:** **SN_Length (km):** **No_ SN_Branch:**			
Time(h)	**Reservoir Head(m)**	**Primary Node Head(m)**	**SN Flow(l/s)**

It is important to note that the parameters that are used to represent the secondary network must be easily obtainable and also sensitive to the behaviour of the networks. In this thesis secondary network data from a representative area were obtained for training ANNs. For the secondary network, the input and output vectors for ANN will take the following form (see Figure 5.2 above)

$x_n = [t_n, h_n, rh_n, l_n, nc_n, ad_n]^T$ -input parameters to the ANN (5.3a)

$a_n = O_n^p = \{Q_n\}$ -predicted secondary network flow for the nth input data set. (5.3b)

l, nc, ad are the length, number of consumers and average demand of a particular secondary network respectively.

t, h, rh are the time of analysis and head at the primary node corresponding to a secondary network and the head at the reservoirs supplying water to network. Q is the flow into the secondary network.

5.4.1.3 Optimal ANN architecture for training

Use of the ANN models for prediction is a very effective but, the accuracy of predictions depends on the structure and complexity of the ANN architecture. It is very important that the ANN model concerned has the appropriate architecture. It is not always possible to come up with the optimal architecture in the first attempt. It is a widely accepted fact that experimentation is required before arriving at the best solution (Swingler, 1996).

The multi layer perceptrons mentioned in this chapter have input, hidden and output layers. The decision to be made when building a MLP concerns the number of layers and number of units contained within each layer. In the application of ANNs to predict pressure dependent demand, inputs and outputs are predetermined as they are selected based on the characteristics of the water distribution system. Generally the ANN architecture will have one input layer with as many units of input parameters and one output layer with number of units equalling the number of outputs. The complication arises in determining the number of hidden layers and the required amount of units each hidden layer would consists of.

When selecting the size of the ANN, there is a trade off between the accuracy of prediction and the complexity or the ability of the network to generalise. The aim of the ANN modeller is to generate an architecture that optimises the generalisation ability of the network. The number of hidden layers must be sufficient for the correct representation of the task (in this instant the secondary network behaviour) but sufficiently low to allow generalisation to take place. There is no simple formula to generate the optimal ANN architecture and no single answer (or architecture). It is always a trial and error process. Hatch-Neilson (1989) stated an approximate upper bound for the number of hidden units as one greater than twice the number of input units. In other words the number of hidden units will not exceed more than twice the number of input units. Martinez *et al.* (2005) employed the following formula to obtain the number of hidden units.

$$J = (N + K)/2 + \sqrt{T} \qquad (5.4)$$

Where J, N, K are the number of hidden, input and output units respectively, T is the number of training vectors

There are number suggestions to determine the number of hidden units in the MLP. However, none of them give the absolute answer. In this chapter, different architectures were tested with the data sets and the one which satisfies the error constraint is taken as the optimal architecture. The different architectures considered and their errors are given in Table 5.2 below. Once optimal architecture for the ANN is obtained, the next step is to train the ANN to represent the secondary network behaviours.

5.4.1.4 Training the ANN with secondary network behaviour

Training an ANN requires data representing the characteristics of secondary network. The data required is obtained from simulating of secondary networks. The secondary network characteristics and the nodal heads are used as the input vector and inflow to the secondary networks is the target output.

The MLP learning is by back propagation of error (Bishop, 1995, Swingler, 1996). The absolute errors (square of the difference between the output and predicted values) are determined and weights adjusted so that the error function is minimized in the direction of the negative gradient of the error surface. Derivative of the errors with respect to weights are used to evaluate the change in weights. This process is continued until the error falls below a prespecified value. The error function of a MLP is given by:

$$MSE = \frac{1}{m}\sum_{t=1}^{m}(T(t) - a(t))^2 \qquad (5.5)$$

Where $T(t)$ is the target output vector at t^{th} iteration or time step, $a(t)$ is the output from the neuron at t^{th} iteration and m is the total number of iteration or (total time).

The back propagation algorithm is obtained by generalising the Widrow-Hoff learning rule to multiple layered networks with non linear differentiable transfer functions. Input and corresponding output vectors are used to train the network until it represents the relationship required.

The LMS algorithm generally known as the Widrow-Hoff learning algorithm is based on an approximate steepest descent procedure. The mean square error is estimated using squared error at each iteration. Weights and biases using the Widrow- Hoff algorithm are given by:

$$w(k+1) = w(k) + 2\alpha e(k)x^T(k) \qquad (5.6)$$

Where α is the learning rate (larger the learning rate, the quicker the training), k is the iteration number (or time step), e is the error at iteration k.

Standard back propagation is a gradient descent algorithm. The term back propagation refers to the way in which the gradient is computed for multilayered networks with non linear functions. There are several variations of basic back propagation algorithm based on different optimisation techniques (Bishop, 1995). In this thesis Levenberg- Marquadt algorithm is selected for the training purpose.

The special feature of Levenberg-Marquardt algorithm is that it generates an approximate Hessian matrix in place of the actual one, to have faster convergence. For feed forward networks the Hessian matrix is approximated as:

$$H = J^T J \qquad (5.7)$$

and the gradient is given as:

$$G = J^T e \qquad (5.8)$$

Where J is the Jacobean matrix of error, e is the vector of network errors

Weights in Levenberg- Marquardt algorithm is given by:

$$w(k+1) = w(k) - \left[J^T J + \mu I\right]^T J^T e \qquad (5.9)$$

Where μ is a scalar which is adjusted to minimise the performance function, I is a unit matrix.

Main drawback of the Levenberg-Marquadt method is that the storage requirement may be high for some matrices (Bishop, 1995). The problem of storage is solved by dividing the Jacobean matrix into two equal sub matrices which are in turn used to calculate the Hessian matrix. Therefore, the full Jacobean matrix does not have to exist at one time.

$$H = J^T J = \begin{bmatrix} J_1^T \\ J_2^T \end{bmatrix} [J_1 \quad J_2] = J_1^T J_1 + J_2^T J_2 \qquad (5.10)$$

The approximate Hessian can be computed by summing a series of sub terms. Once a sub term has been computed the corresponding sub matrix of the Jacobean is cleared (Bishop, 1995).

5.4.2 Integration of ANN with Network Analysis Program

ANNs are trained to predict the pressure dependent flows into the secondary networks, in other words secondary networks at primary nodes are replaced by ANNs. The role of ANN in pressure dependent demand analysis very much similar to that of pressure dependent function, but differs in that ANNs learn the secondary network behaviour. Incorporating the ANN with the network analysis program has the same procedures as incorporating the ordinary PDD functions. The additional term in the Jacobean matrix as shown in Chapter 4, Section 4.3 equation 4.13 would be the derivative of the PDD relationship developed by the ANN. However, the main draw back of the PDD relationship generated by the ANN is that it does not have an explicit function and as a result, analytical methods cannot be used to evaluate the derivative.

Therefore, to evaluate the derivative of the PDD relationship or a given head, numerical differentiation techniques need to be employed. Equation 5.10 below shows how the pressure dependent relationship obtained by the ANN is incorporated with the nodal flow continuity equation. Here a relationship $\Phi_i(H_i)$ is assumed for the PDD relationship developed by the ANN in order to demonstrate the process of integrating ANN with network analysis.

$$F_i(H_i, H_j) = \sum_{j \in J_i} \left\{ R_{ij} \operatorname{sgn}(H_i - H_j) \left| H_i - H_j \right|^{0.54} \right\} + \Phi_i(H_i) \qquad \forall i \in NPN \qquad (5.11)$$

Where H_i and H_j are the nodal heads of nodes *i* and *j*; *sgn(X)* is the sign of X; R_{ij} represents the conductivity of the pipe connecting nodes *i* and *j* (related to diameter, length and *C* value); Φ_i is the ANN generated PDD for node *i* and; J_i are all the nodes connected to node *I*, *NPN* is the number of pressure nodes.

The central difference method of evaluating the derivative of the ANN relationship is shown below in the equation 5.11:

$$\frac{\partial \Phi_i}{\partial H_i} = \frac{\Phi_i(H_i + \Delta H_i) - \Phi_i(H_i - \Delta H_i)}{2\Delta H_i} \quad (5.12)$$

Where $q(H_i + \Delta H_i)$, $q(H_i)$, $q(H_i - \Delta H_i)$ and $(H + \Delta H)$, H, $(H - \Delta H)$ are the flows and their corresponding heads at the node i and ΔH is the difference in nodal head.

The elements of the Jacobean matrix take the form shown below:

$$\frac{\partial F_i}{\partial H_j} = -0.54 R_{ij} \left| H_i - H_j \right|^{-0.46} \quad (5.13a)$$

$$\frac{\partial F_i}{\partial H_i} = \sum_{i \in J} \left\{ 0.54 R_{ij} \left| H_i - H_j \right|^{-0.46} \right\} + \frac{\partial \Phi_i(H_i)}{\partial H_i} \quad (5.13b)$$

The remaining steps are same as that of demand driven formulation.

Interaction between the ANN and the network analysis program is shown in the Figure 5.8 shown below.

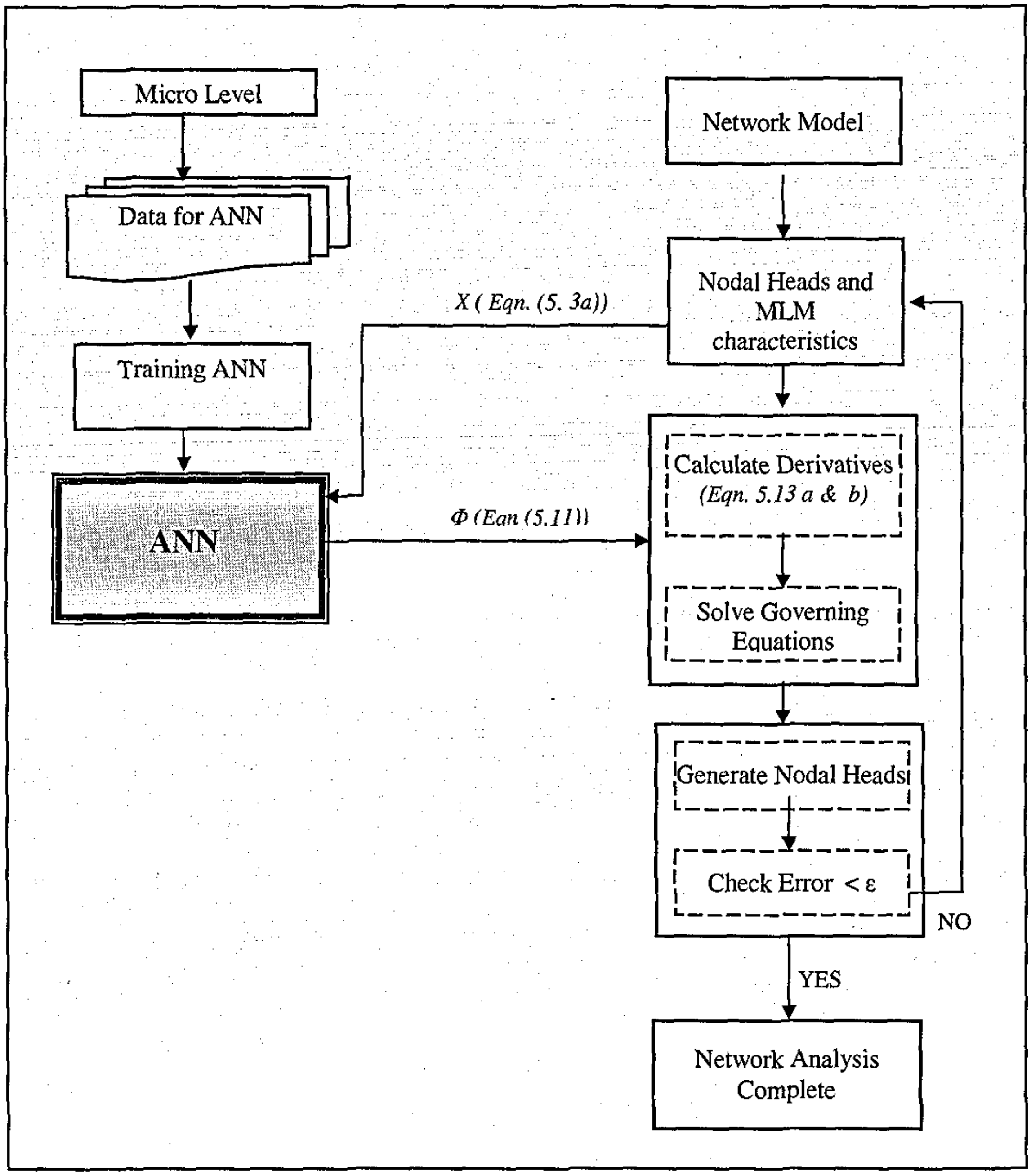


Figure 5.8: Interaction of ANN with network analysis

In the Figure 5.8 primary role of the ANN model is to estimate the nodal flows corresponding to the heads produced by the steady state model. These flows are in turn used to evaluate the all important derivative needed to build the Jacobean matrix. In order to understand the temporal variations in the network an Extended Period Simulation (EPS) is required.

The analysis of WDS using the proposed network analysis is very similar to the conventional network analysis with pressure dependent demand functions. The integration of the ANN with the network analysis has the additional advantage of simulating the secondary network characteristics and also takes the local plumbing arrangements into account. Although this program is applicable to all situations, it is not necessary to use this during normal operations as the conventional demand driven method predicts very reasonable nodal heads and outflows.

The ANN based network analysis model and the MLM based model (chapter 4) are fundamentally same. The difference is that the ANN model replaces the individual MLM attached to each primary node of the WDS. To evaluate the performance of the proposed network analysis program, it has been applied to a network.

5.5 Application ANN Method to a Network

The same 30 node network given in chapter 2 is used to demonstrate the applicability of the ANN models in predicting pressure dependent demand in water distribution systems. In this study 28 different secondary networks were modelled (one for each demand node) out of which total of 5000 data sets were randomly picked to train the ANN. The Secondary network data were divided into three parts; 50% for training, 25% for testing and the rest was for cross validation. Different architectures were considered for the ANN training and their efficiencies compared by trial and error method, which are given in Table 5.2. From Table 5.2 it can be seen that the least mean square error in training is given by the 7-11-1 (7 input, 11 hidden and 1 output layers) network with hidden and output layers consisting of hyperbolic tangent and linear functions respectively. The MSE were calculated using equation 5.7 for 1000 runs for each architecture. Figure 5.9 indicate the error during training, testing and cross validation. The training process is stopped at 143 epochs. At this instant the validation error starts to increase, where the network is said to be generalised to simulate any condition.

Table 5.2: Architecture and performance of ANNs

Training Parameter	Architecture	Epochs(no of runs)	Error(MSE)
t,h, nc	3-5-1	223	3.06
t,h, nc	3-10-1	439	$2.75*10^{-1}$
t,h, nb	3-5-1	168	6.75
t,h, nb	3-10-1	239	2.18
t,h, ad	3-5-1	389	$5.54*10^{-1}$
t,h, ad	3-10-1	550	$2.59*10^{-1}$
t,h, l	3-5-1	1050	3.15
t,h, l	3-10-1	862	$2.70*10^{-1}$
t,h, ad,n	4-5-1	426	$3.44*10^{-1}$
t,h, ad,n	4-10-1	353	$1.15*10^{-2}$
t,h, ad, l	4-5-1	238	$3.10*10^{-1}$
t,h, ad, l	4-10-1	140	$2.07*10^{-1}$
t,h, ad, n, l	5-5-1	224	$3.11*10^{-2}$
t,h, ad, n, l	5-10-1	188	$1.73*10^{-2}$
t,h, ad, nc ,nb , l	6-10-1	183	$7.10*10^{-2}$
t,h, ad, nc, nb, l	6-11-1	219	$7.35*10^{-2}$
t,h, ad, nc ,nb ,rh, l	7-10-1	237	$1.35*10^{-1}$
t,h, ad, nc, nb, rh, l	7-15-1	203	$4.11*10^{-2}$
t,h, ad, nc, nb, rh, l	7-11-1	143	$1.35*10^{-3}$

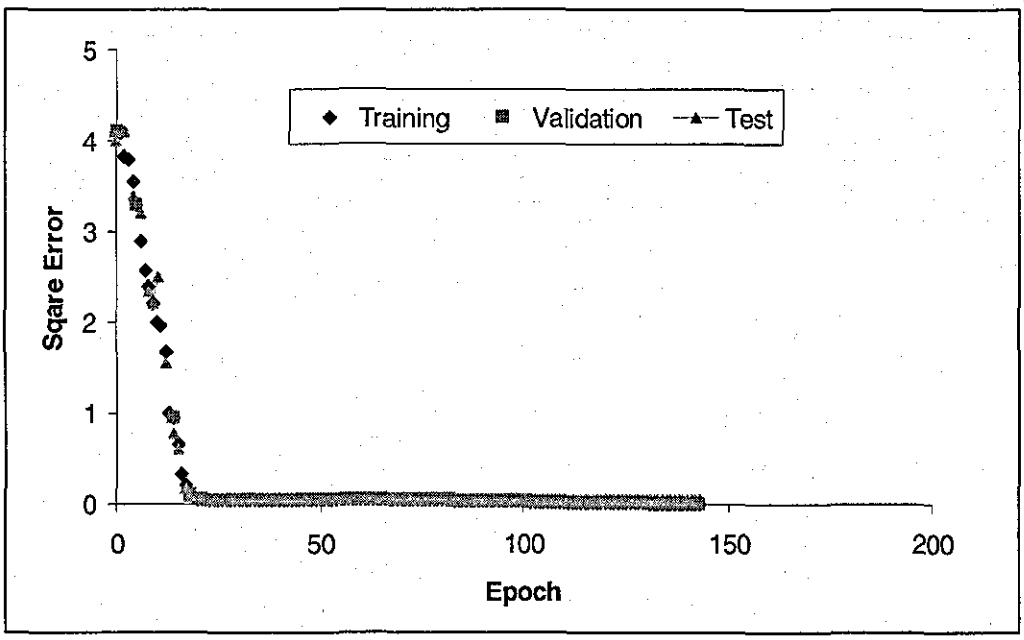


Figure 5.9: Error analysis plot during the training of the ANN

To compare the ANN model and the micro level models during normal operation of the network, simulation of the WDS is performed. To demonstrate the applicability of ANN model when applied to a failure, in this example a simple pipe burst is simulated in pipe 23 (between nodes 18& 20). Clearly the consequence of this failure is a sudden drop in pressure and as a result redistribution of flows. Both ANN and MLM are expected to give similar results with very little variations.

5.5.1 Results

Figures 5.10-5.13 show the simulation results of the MLM and the ANN models for selected nodes. The nodal heads, outflows and the percentage variations are plotted for each analysis method (ANN method and MLM method). These figures also show the results during normal operation. Figures 5.14 - 5.17 give that of during an extreme event at time step (pipe 23 burst) 9. AM.

Normal Operation

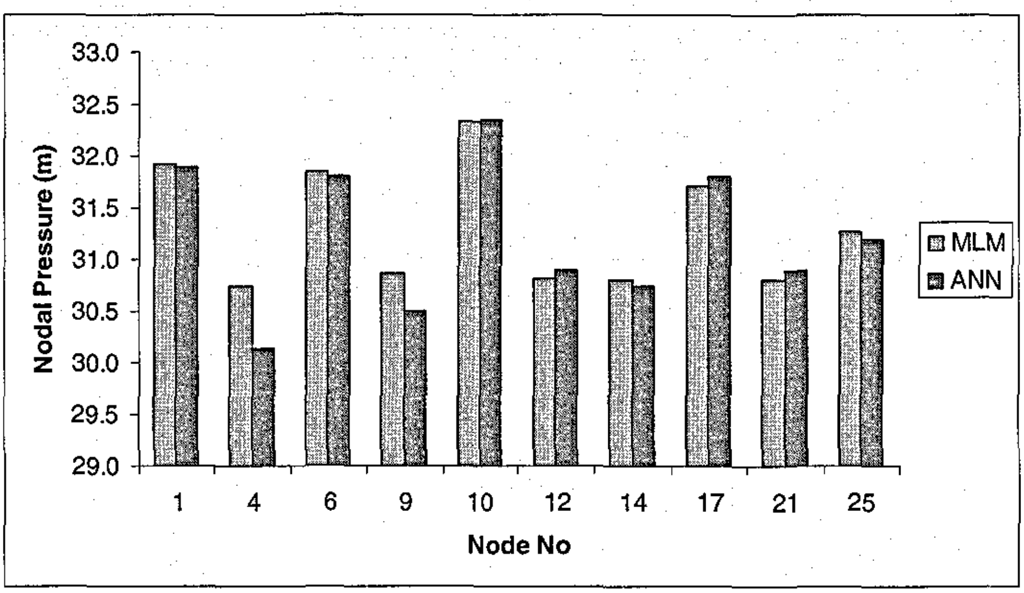


Figure 5.10: Heads at node (Normal operation-9 AM)

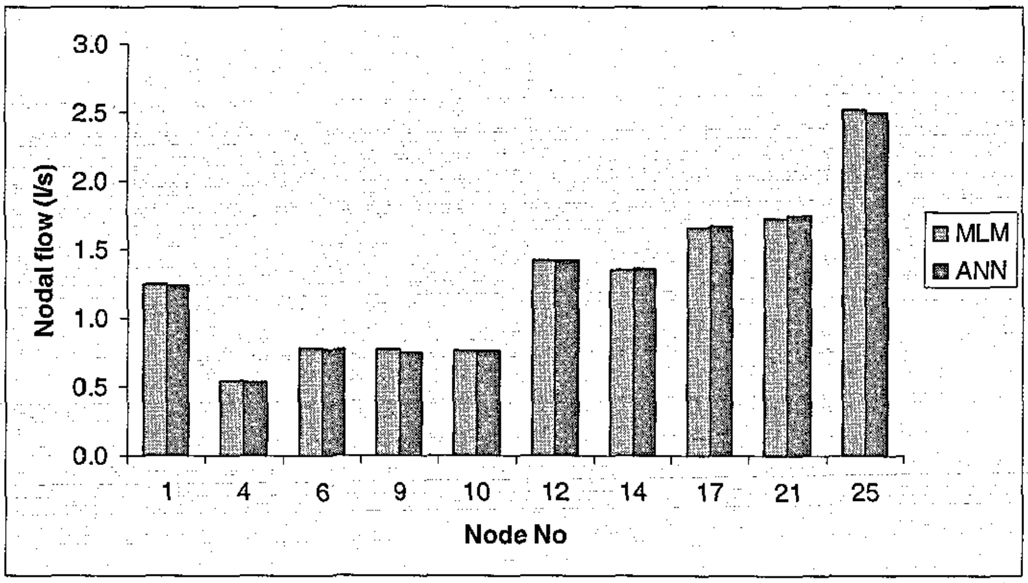


Figure 5.11: Flows at node (Normal operation-9 AM)

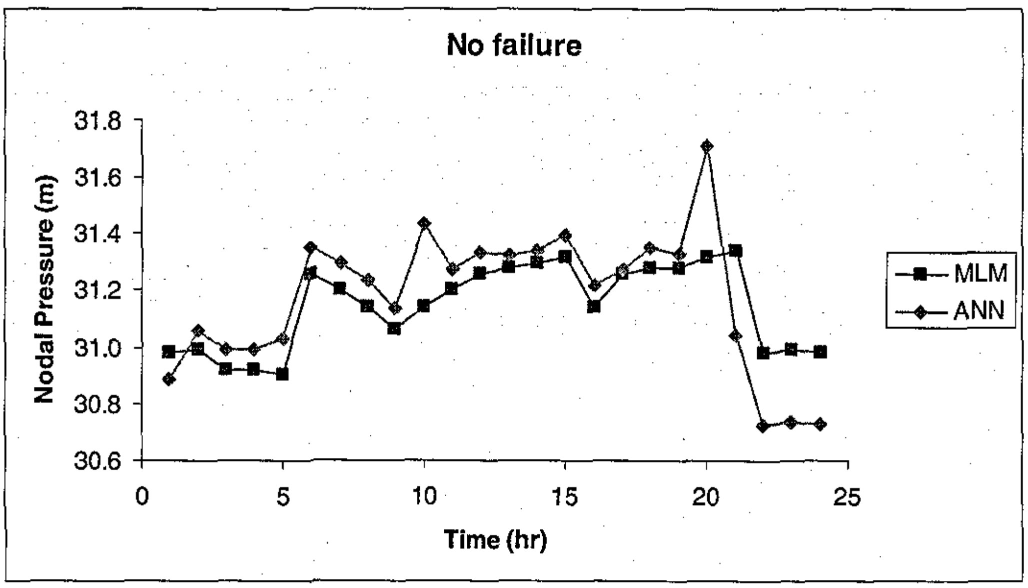


Figure 5.12: Variation in heads and flows of MLM and ANN models (Normal operation)

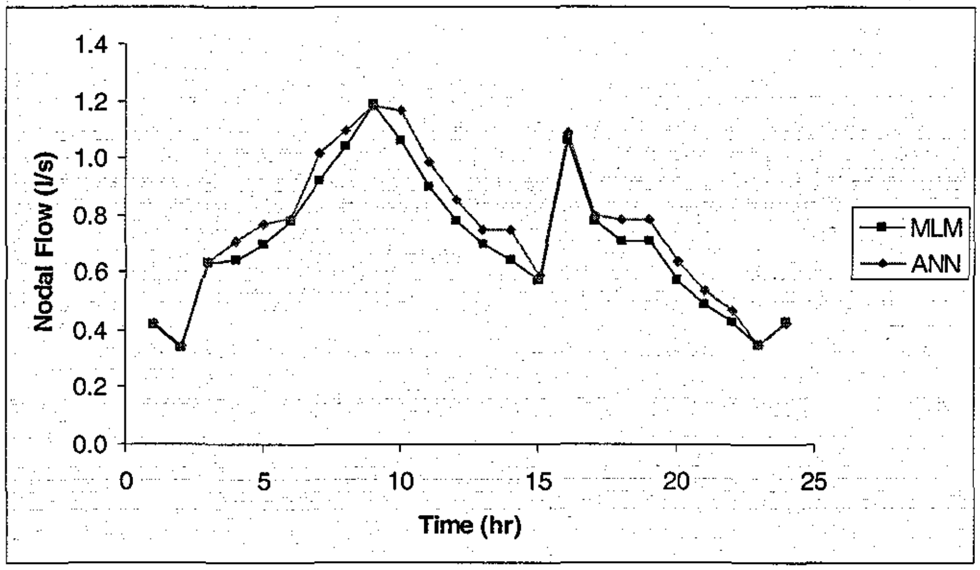


Figure 5.13: Variation in heads and flows of MLM and ANN models (Normal operation)

Failure

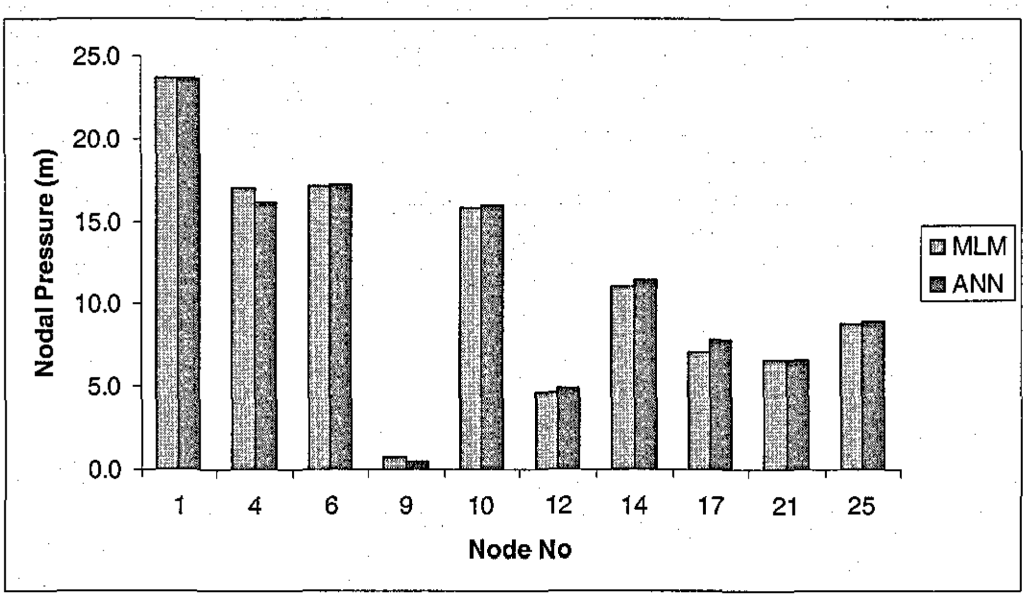


Figure 5.14: Heads at node (Failure-9AM)

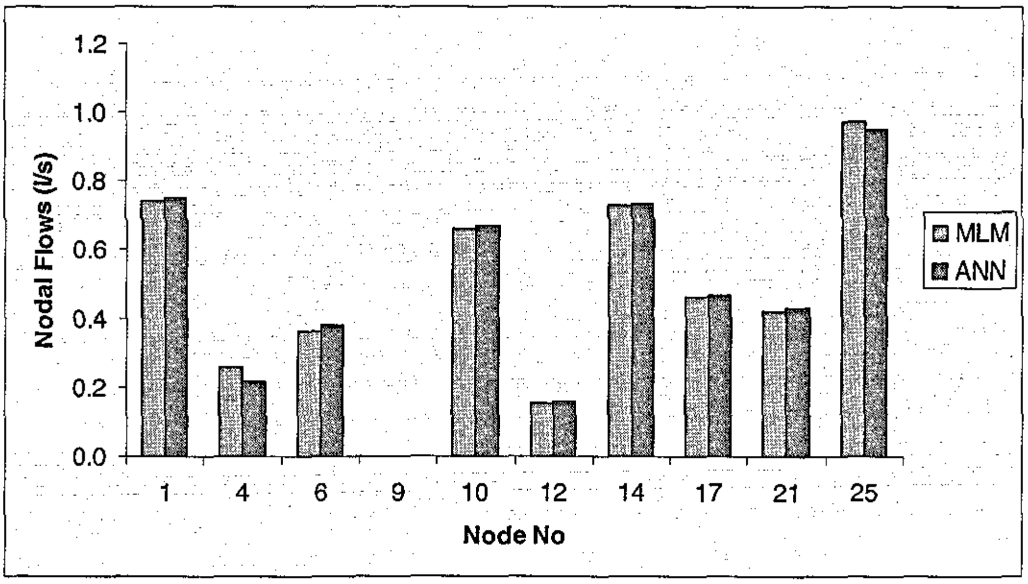


Figure 5.15: Flows at node (Failure-9AM)

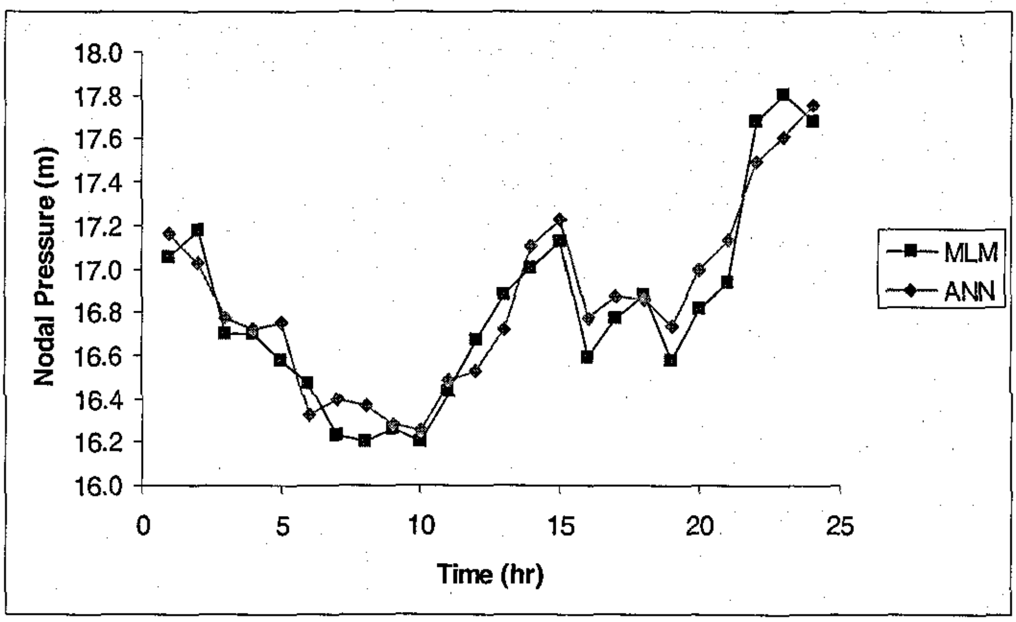


Figure 5.16: Variation in heads of MLM and ANN models (Failure)

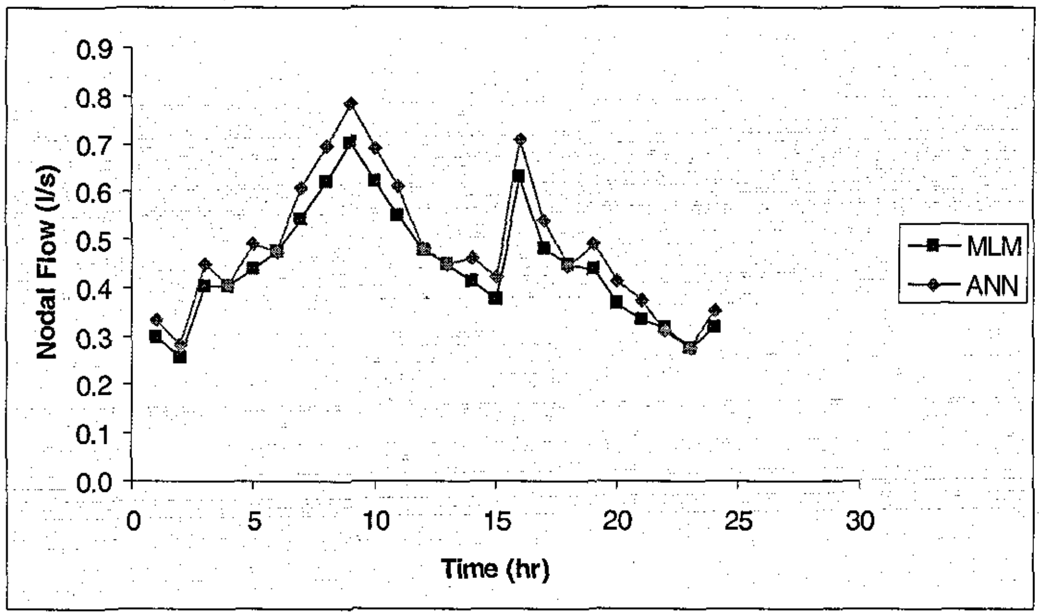


Figure 5.17: Variation in flows of MLM and ANN models (Failure)

5.5.2 Comparison

Figures 5.10 and 5.13 shows that both ANN method and micro level analysis methods give very similar nodal heads and flows during normal operating condition. It was observed that the variation in the heads and the flows at nodes between the two methods fall below 5%. Therefore, the predictions of MLM and ANN methods are very similar during normal operations.

Also from Chapter 4, the demand driven and the MLM analysis of WDS for normal operational conditions produced very similar nodal outflows and pressures. Therefore, ANN, MLM and demand driven approaches all are applicable to WDS during normal operations of the network.

When the failure was simulated on pipe 23, the pressures and corresponding flows at nodes are shown in Figures 5.14-5.17. Unlike the DD model both MLM and ANN models show that there is a shortfall in flow due to the drop in pressure at nodes. Furthermore, the differences in values of flows and pressures between the two methods are on average below 5%. This indicates that during an extreme situation both the MLM and the ANN models predict the same results with very small variations.

During the normal operations and also during failure events, the ANN model and the MLM approach predicts the pressure dependent nodal outflows. The slight variations in the flow and pressure between the ANN and MLM models are due to the modelling errors and assumption during building the MLM. However, the extent of modelling errors will be minimal in the ANN model as it is based only on data from the secondary network and no model is required.

It was mentioned earlier that the MLM are the closest approximate model to the real WDS because they incorporate the secondary networks corresponding to each primary node. Also from the simulation results, it is evident that the predictions of the ANN model are very close to that of the MLM model. Therefore, the ANN model is good alternative to analyse the network conditions especially in the events of failures or extreme events in the water distribution systems.

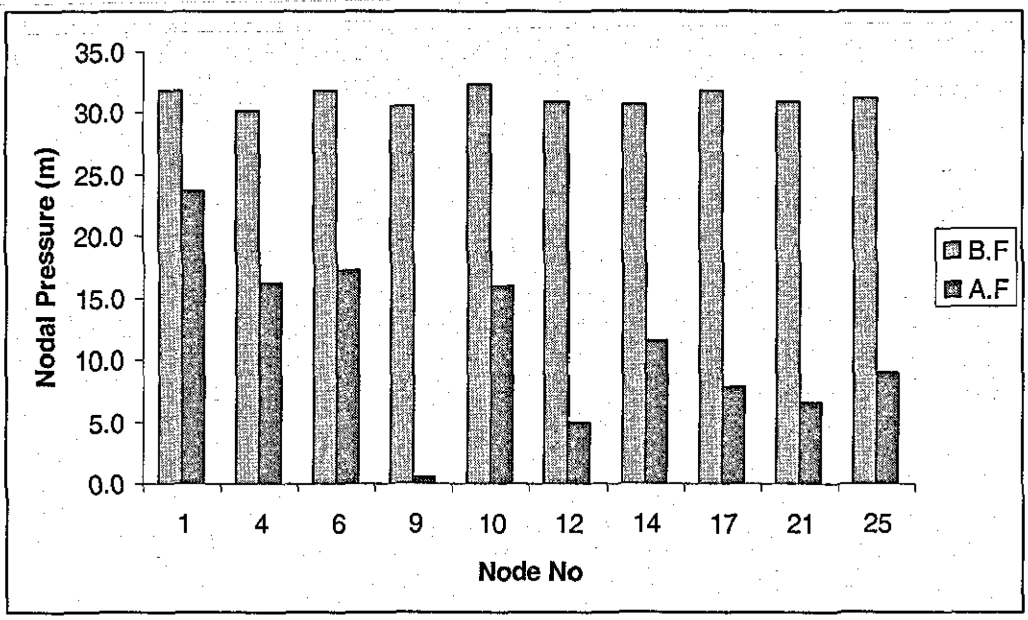


Figure 5.18: Heads at node before and after failure for ANN

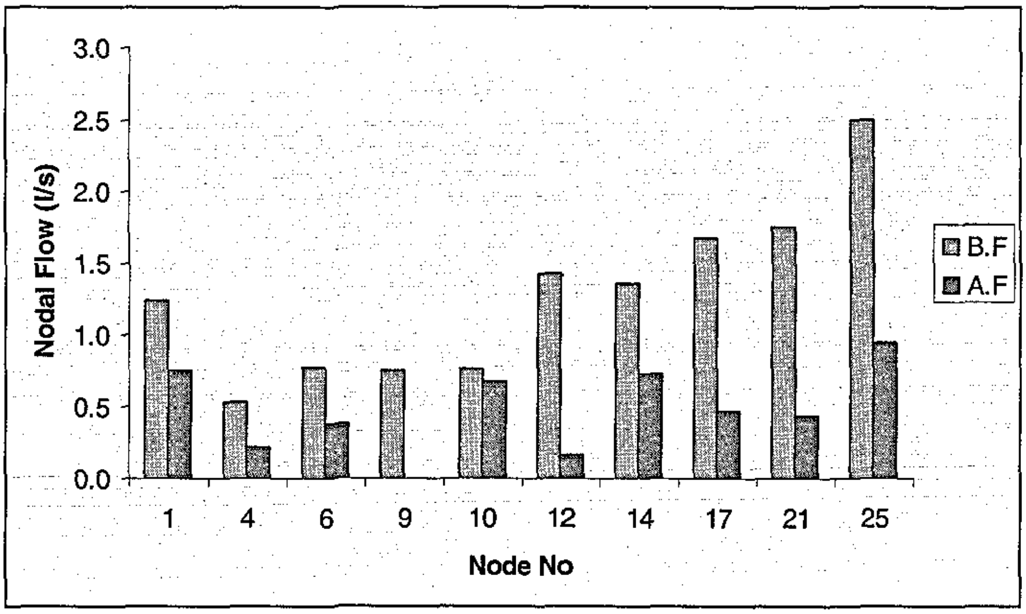


Figure 5.19 Flows at node before and after failure for ANN

Figures 5.18 and 5.19., shows the nodal pressures and flows just before and just after the failure events respectively. These figures indicate the flow variations at nodes corresponding to the pressure variations as a result of failure events.

5.6 Conclusion

This chapter introduces the artificial neural network based network analysis method to analyse pressure dependent demand behaviour of water distribution systems, especially during extreme (or failure) situations.

The selection of appropriate type of artificial neural network and architecture were explained and the integration of ANN with network analysis program is described in detail.

The performance of the ANN and the MLMs in analysing extreme events in water distribution systems were compared. Advantages of ANN method over existing pressure dependent demand functions are highlighted. Furthermore, the issue of applying MLMs to large size networks is dealt with by introducing artificial neural networks. The use of ANNs becomes essential to simplify the network model rather than having secondary networks at each node. Therefore, each secondary network is replaced by an ANN.

In this section ANN is used as a black box model. ANNs are trained to simulate the behaviour of secondary networks and incorporated in network analysis program to predict nodal outflows. Training data required for the ANN include secondary network characteristics (length of the network, number of consumers, average demand etc.), time, head and corresponding flow.

Developed ANN model is applied to a 30 node network and simulations performed during normal operations and extreme events (failures). The results were compared mainly with micro level models to assess the performance of the ANN based network analysis model. The outcome of the simulations indicated that during normal operational conditions the MLM and the ANN based network analysis predicted similar results. Applying both the methods to a network with a failure event produced less flows and pressures than during normal operations but the predicted flows and their corresponding pressures were very similar for both ANN based model and MLM.

It was shown in chapter 4 that MLM models to analyse pressure deficient WDS are more appropriate than applying PDD functions. In this chapter it has been shown that ANN based network analysis and MLM based network model both behave similarly during normal operations and also during failure events in WDS. Furthermore, integration of the ANN with the network analysis provides the ability to apply the MLM to larger and more complex WDS by way of training the ANNs with the MLM characteristics.

The principal conclusions of this chapter are:

- Behaviour of secondary networks in the WDS is trained using ANNs.
- MLMs were represented by their characteristics such as length, diameter, average demand and number of consumers.
- ANNs are trained with the characteristics of only a few selected secondary networks from the WDS.
- The Jacobean matrix of the ANN is obtained by using a central difference method.
- ANN based network analysis is more appropriate to apply to large and complex WDS than the micro level models.
- Both MLM and ANN based network analysis models are applicable only if secondary network information is available.

CHAPTER 6

SIMULATION AND APPLICATION

6.1 Introduction

The thesis so far has tried to illustrate the individual components of the performance assessment model. The pressure dependent demand analysis method, component failure prediction and the performance measures combined together results in the performance assessment model. The interaction between the three models is important to apply the performance assessment model to WDS. This chapter describes the integration of the three individual components.

This chapter mainly focuses on the application of the performance assessment methodology to a case study water distribution system. The case study network is located in the Severn Trent utility area (greater Birmingham area including the Solihull metropolitan borough council area, Olton and Acocks Green).

In order to demonstrate the methodology, the water distribution network was analysed using the demand driven method, the micro level method and the proposed methodology. Failure simulations are carried out using PDD analysis and the proposed ANN based method. Components for the failure simulations are selected using the component failure prediction model. The results from the network analysis are fed into the performance measures and the results discussed.

6.2 Performance Assessment Model

The aim of the performance assessment model is to evaluate and quantify the consequences due to failure events in water distribution systems. The performance assessment model developed in this thesis consists of three individual components namely:

- The component failure prediction model
- The hydraulic simulation model
- The performance measures

Detail descriptions of each of the above models have been given in earlier chapters. This chapter attempts to explain the integration of the individual components that makes the performance assessment model.

The sequence involved in applying the individual models starts with the use of component failure prediction model followed by hydraulic simulation model and performance measures. This order is illustrated in Figure 6.1 below. Component failure events including the failure time, the failure duration and the repair durations are generated by the failure prediction model.

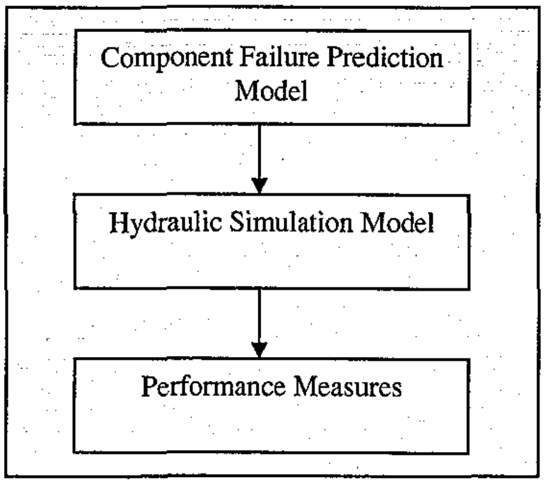


Figure 6.1: Performance assessment model

The failure event is then represented in the hydraulic simulation model so that the hydraulic model can simulate the network behaviour. The method used to represent the failure events in WDS influence the predictions from the hydraulic model. For example, a pipe failure in a WDS can be represented either by just isolating the pipe or by more accurately representing the dynamic failure (immediately after failure) and the isolation (for repair) stages. The method used in this thesis to representing component failures in WDS is given below.

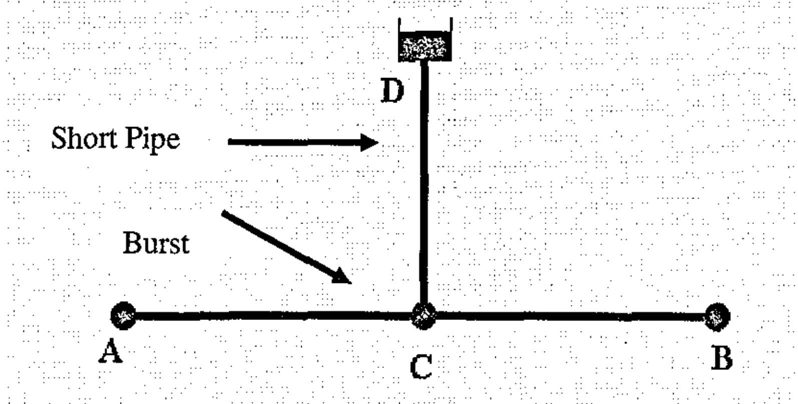
6.3 Representing a Failed Component

The two types of component failures discussed here are the pump and the pipe failures. The pump failures are sudden events and can occur due to various reasons. Power outages and seizing of pump components are a few but to mention. Generally a pumping station will have backup pumps that will come into action as soon as a pump goes out of service. Therefore, the pump failures in WDS are less frequent events.

Representing a pump failure in the water distribution system is by just shutting down the pump using the controls in the network analysis program or by giving a pump operation pattern where the pattern will indicate the times at which pump stop.

Unlike pumps, pipe failures are complicated as there are three states to be represented. Furthermore the flow out of a burst will be pressure dependent. Germanopoulos (1988); Vairavamoorthy (1990); Mansoor and Vairavamoorthy (2005) used the following arrangement shown in Figure 6.2 to represent a pipe burst in the water distribution system.

The short pipe is connected to the main pipe at the point where the burst is to occur. A constant head reservoir is attached to the end of the short pipe. The water level in the reservoir is equal to the elevation of the main pipe at the point where the short pipe connects with it. The burst is simulated by setting controls to open and shut the pipes.



Before burst:-Pipe AB open and CD is closed
During burst: - Pipe AB open and CD is open
During isolation:-Pipe AB is closed

Figure 6.2: Simulation of a pipe burst

The flow during the burst can be represented by:

$$q = \sqrt{\frac{h}{K}} \qquad (6.1)$$

Where q is the flow from the burst (through the short pipe), h is the pressure at the burst, K is the conductivity of the (short) pipe, depends on diameter, roughness and length.

Equation (6.1) suggests that the flow from the burst is an orifice flow and depends on the pressure at the burst.

6.4 Integration of the Three Models

The three components of the proposed performance assessment model communicate with each other during the failure assessment process.

Initially the failure prediction model generates the possible component failure events that may occur in the WDS. Out puts of this model are: the component inter failure times, the frequency of failures, the failure and the repair times. This information is needed to model the failure events with the hydraulic model. Each failure event is represented as explained in section 6.3 above and a network analysis is performed to understand the behaviour of the WDS. The ANN based network analysis program will determine the pressure dependent nodal outflows of the WDS due to the failure event. Outputs from the network analysis program are passed on to the performance measures where a set of performance measures will be generated based on the nodal flows and pressures at the WDS. Interaction between the component failure model, the hydraulic network analysis model and the performance measures are illustrated in the Figure 6.3 below.

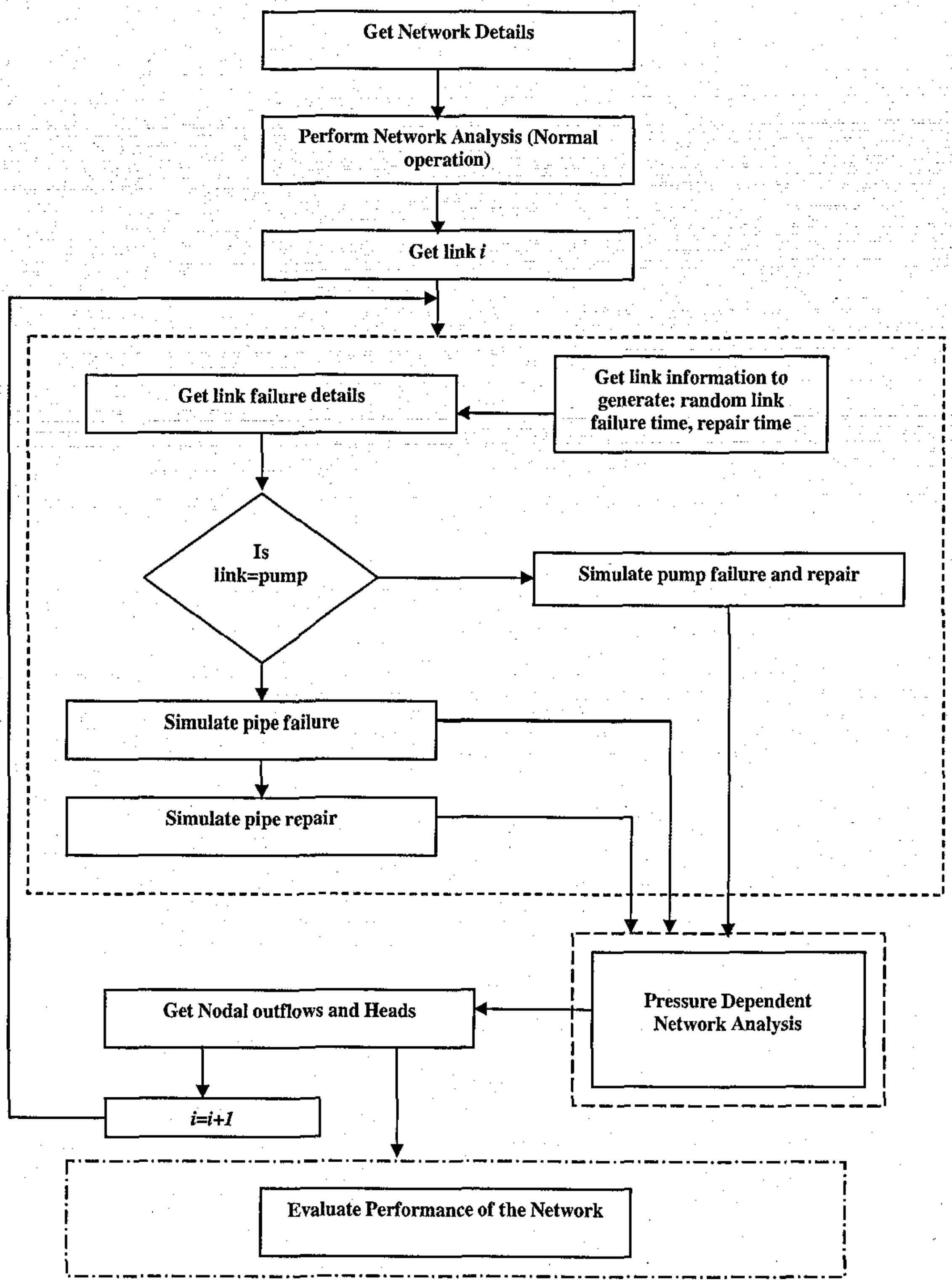


Figure 6.3: Step by step approach of performance assessment

6.5 Case Study

The applicability of the ANN based network analysis program is demonstrated by applying it to a case study.

The water distribution network considered in this thesis is located in the suburbs of Birmingham, in particular in the areas of Solihull, Olton and Acocks Green. This area fall within 7 miles from the Birmingham city centre. Out of the three areas considered, Solihull and Olton lies within the Solihull metropolitan area and Acocks Green is a ward of South Birmingham. The case study area is in the Severn Trent water supply area.

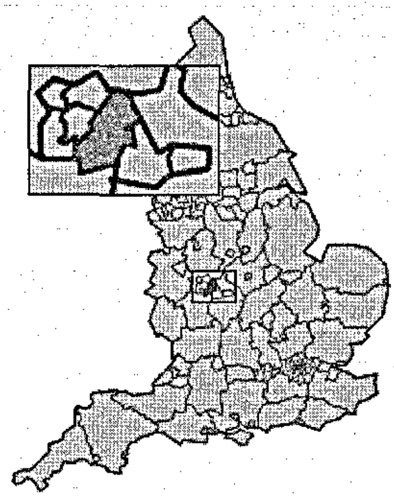


Figure 6.4: Birmingham Area (shaded)

The Birmingham city is located to the west of the geographical centre of England. The OS grid reference and the coordinates of the city are "SP066868" and "52° 29N and 1° 54W" respectively. The city is at relatively high grounds, ranging around 150-200 metres above sea level. UK's main north-south watershed passes through this area.

6.5.1 Network Details

The section of water distribution network supplying this area is shown in Figure 6.4 above. This network has been developed from scratch using the information obtained from the ordinance survey maps and the local knowledge. The reason for developing this network is that the existing network does not have detail information on secondary networks. The pipe sizes were obtained by performing an optimisation using the Opti designer software. The network details and its associated secondary networks have been given in the Appendix 3. However, some details relevant to component failure prediction are given in Table 6.1 below.

The per capita demands of Solihull, Olton and Acocks Green are all assumed to be 137 lpcd which conforms to the average per capita consumption for Severn Trent water supply area (OFWAT, 2007). The usage sequence of the consumers is assumed to follow that given in Chapter 4.

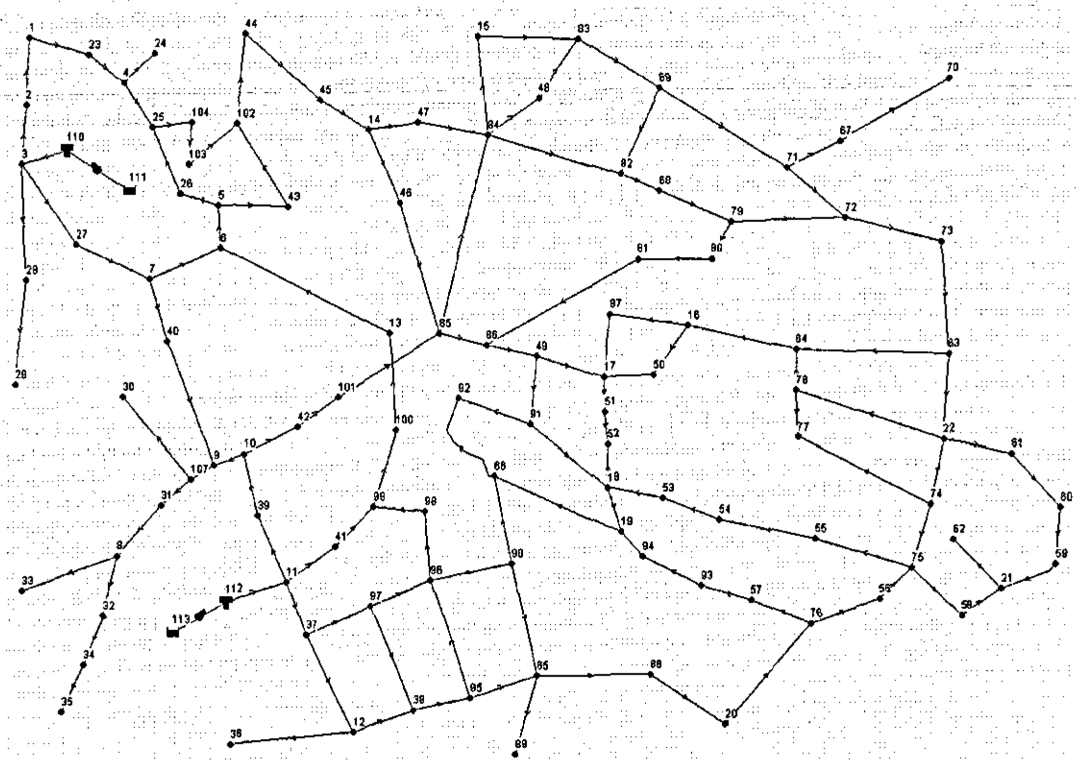


Figure 6.5: Case study network

The consumers distribution across the network interms of income level and consumption are determined by way of field visists and also from the Solihull metropolitan borrough council. This information is important in generating weights for the severity measure that was proposed in chapter 2. The process involed in generating the weights has been described in detail in Chapter 2 and Appendix 1.

Table 6.1a: Link details of the case study network

Pipe No	Length (m)	Diameter (mm)	C Value	MTBF (year)	Pipe No	Length (m)	Diameter (mm)	C Value	MTBF (year)
1	1040	300	100	9.62	51	608	100	100	2.35
2	640	300	100	3.13	52	400	300	100	5
3	640	300	100	5.21	53	320	300	100	6.25
4	360	300	100	9.26	54	640	300	100	3.13
5	240	200	100	6.95	55	752	100	100	1.9
6	272	300	100	9.2	56	544	100	100	2.63
7	128	300	100	15.63	57	544	200	100	2.63
8	160	300	100	12.5	58	576	300	100	3.48
9	432	300	100	4.63	59	592	100	100	2.42
10	272	300	100	3.68	60	624	100	100	2.29
11	640	250	100	2.24	61	352	250	100	4.06
12	720	250	100	1.99	62	320	250	100	4.47
13	640	300	100	3.13	63	768	300	100	2.61
14	560	300	100	3.58	64	944	300	100	2.12
15	640	300	100	3.13	65	672	300	100	2.98
16	480	300	100	4.17	66	480	300	100	4.17
17	752	300	100	2.66	67	480	300	100	4.17
18	400	300	100	5	68	960	200	100	1.49
19	480	300	100	4.17	69	240	300	100	8.34
20	1152	300	100	1.74	70	560	300	100	3.58
21	560	300	100	3.58	71	320	300	100	6.25
22	512	200	100	2.8	72	464	300	100	4.32
23	640	100	100	2.24	73	1040	200	100	1.38
24	208	100	100	6.87	74	960	300	100	2.09
25	496	100	100	2.89	75	160	300	100	12.5
26	224	100	100	6.38	76	560	300	100	3.58
27	368	300	100	5.44	77	528	300	100	3.79
28	450	300	100	4.45	78	1200	200	100	1.2
29	128	100	100	11.17	79	480	150	100	2.98
30	432	300	100	4.63	80	192	150	100	7.45
31	352	300	100	5.69	81	416	150	100	3.44
32	640	300	100	3.13	82	1000	150	100	1.43
33	320	300	100	6.25	83	512	300	100	3.91
34	608	300	100	3.29	84	160	300	100	12.5
35	688	100	100	2.08	85	528	300	100	3.79
36	112	100	100	12.76	86	352	150	100	4.06
37	640	200	100	2.24	87	928	150	100	1.54
38	304	100	100	4.7	88	640	300	100	3.13
39	192	100	100	7.45	89	448	300	100	4.47
40	672	100	100	2.13	90	320	300	100	6.25
41	416	250	100	3.44	91	1232	150	100	1.16
42	560	300	100	3.58	92	480	300	100	4.17
43	624	300	100	3.21	93	480	300	100	4.17
44	576	200	100	2.49	94	832	300	100	2.41
45	1488	100	100	0.97	95	112	300	100	17.86
46	912	300	100	2.2	96	464	300	100	4.32
47	512	300	100	3.91	97	432	300	100	4.63
48	512	300	100	3.91	98	592	300	100	3.38
49	352	300	100	5.69	99	560	300	100	3.58
50	416	300	100	4.81	100	352	300	100	5.69

Table 6.1b: Link details of the case study network

Pipe No	Length (m)	Diameter (mm)	C Value	MTBF (year)	Pipe No	Length (m)	Diameter (mm)	C Value	MTBF (year)
101	464	300	100	4.32	117	112	100	100	12.76
102	176	300	100	11.37	118	528	100	100	2.71
103	544	300	100	3.68	119	80	300	100	25
104	592	300	100	3.38	120	272	300	100	7.36
105	560	300	100	3.58	121	688	300	100	2.91
106	272	150	100	5.26	122	672	150	100	2.13
107	208	300	100	9.62	123	512	100	100	2.8
108	672	300	100	2.98	124	640	100	100	2.24
109	864	300	100	2.32	125	672	100	100	2.13
110	160	100	100	8.93	126	800	100	100	1.79
111	320	100	100	4.47	127	462	300	100	4.33
112	320	100	100	4.47	128	500	300	100	4
113	384	100	100	3.73	129	300	100	100	4.77
114	336	300	100	5.96	130	660	100	100	2.17
115	240	300	100	8.34	131	250	300	100	8
116	228	150	100	6.27	132	250	300	100	8

6.5.2 Failure Prediction

The component failure events were generated using the Monte Carlo method given in chapter 3. The pipe inter failure times were given in the Table 6.1 and the pipe inter failure times are assumed to follow an exponential distribution and the pipe repair durations are assumed to follow a uniform distribution between 5 and 72 hours. These assumptions are consistant with that of Wagner *et al.* (1988b). In this analysis 50% of the pipe repair times are allocated for isolation of the failed pipe, in other words just after failure, half the repair time is needed to locate the pipe burst and to isolate it inorder for it to be repaired. It should be noted that data on pipe isolation times are very rare as most water utilities record only pipe repair times and statistical characteristics of pipe isolation times are yet to be deterimined. Isolation times vary depending on the location and acceesibility and the time taken to isolate a pipe have an influence on the performance of the WDS. In this section, the main objective is to demontrate different phases of pipe failures (failure,isolation and repair) therefore, assuming 50% of repair time for pipe isolation is only for the purpose of demonstrating the isolation phase.

Randomly generated component failure events and their corresponding failure and repair durations are given in Table 6.2. This table consists details of only 35 pipes, remaining failures are given in Appendix 3.

Table 6.2: Random Pipe failure details

Pipe No	Failure1		Failure2		Failure3		Failure4	
	FT(days)	RD(hours)	FT(days)	RD(hours)	FT(days)	RD(hours)	FT(days)	RD(hours)
1	949.6	10	1642.5	23	1825.7	48	3286.7	11
2	2993.4	56	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0
4	876.5	7	2007.5	18	3577.3	70	0	0
5	2190	66	0	0	0	0	0	0
6	2080.5	29	0	0	0	0	0	0
7	348	36	0	0	0	0	0	0
8	2372.5	12	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0
10	766.5	9	1898	23	0	0	0	0
11	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0
13	474.5	15	730	60	0	0	0	0
14	1460	43	1861.5	24	0	0	0	0
15	2555	13	0	0	0	0	0	0
16	547	20	2263	5	0	0	0	0
17	2628.3	16	3759.5	8	0	0	0	0
18	912.5	27	1095	19	2701.6	22	0	0
19	0	0	0	0	0	0	0	0
20	2847	50	0	0	0	0	0	0
21	3102	44	3686.5	14	0	0	0	0
22	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0
25	1131.5	55	0	0	0	0	0	0
26	693.4	67	1204.6	6	2810.5	71	0	0
27	0	0	0	0	0	0	0	0
28	0	0	0	0	0	0	0	0
29	2226.5	22	0	0	0	0	0	0
30	1934.3	11	0	0	0	0	0	0
31	3438	9	0	0	0	0	0	0
32	510.3	16	2425.4	30	0	0	0	0
33	211.5	23	2533.5	52	0	0	0	0
34	0	0	0	0	0	0	0	0
35	3110.2	17	0	0	0	0	0	0

The network was simulated for 10 years, during that period of operation. The maximum number of random failure events generated by the program for a single pipe is 4. Some of the pipes did not have any failures. It is also noted that in this network pipes did not encounter simultaneous failure events (two pipes failing at the same time) however, such situations might arise if the simulation period is large (say 100 years).

6.5.3 Training ANN for the PDD Analysis

In order to perform the hydraulic analysis of the case study network, the ANNs were trained to obtain the optimal architecture. 10% of the secondary networks were randomly selected and their caharacteristics identified for training purposes. The table 6.3 gives typical ANN architectures corresponding to input parameters. In this case study 12,000 data sets were obtained from the secondary networks. 50% of the data were used for training, 25% of the data for testing and the remaining for cross validataion. Figure 6.6 shows the performance of the optimal ANN during the training process.

Table 6.3 Architectures used for training the ANN

Training Parameter	Architecture	Epochs(no of runs)	Error(MSE)
t ,h, ad, nc ,nb , l	6-10-1	218	$9.10*10^{-2}$
t ,h, ad, nc, nb, l	6-11-1	315	$8.11*10^{-2}$
t ,h, ad, nc ,nb ,rh, l	7-10-1	197	$5.5*10^{-1}$
t ,h, ad, nc, nb, rh, l	7-15-1	255	$6.0*10^{-2}$
t ,h, ad, nc, nb, rh, l	7-11-1	190	$4.15*10^{-3}$
t ,h, ad, nc ,nb , l	6-10-1	205	$5.3*10^{-2}$
t ,h, ad, nc, nb, l	6-11-1	290	$3.32*10^{-2}$
t ,h, ad, nc ,nb ,rh, l	7-10-1	178	$1.5*10^{-1}$
t ,h, ad, nc, nb, rh, l	7-15-1	210	$3.1*10^{-2}$
t ,h, ad, nc, nb, rh, l	7-11-1	195	$2.3*10^{-3}$
t ,h, ad, nc ,nb , l	6-10-1	200	$7.55*10^{-2}$
t ,h, ad, nc, nb, rh, l	7-12-1	183	$1.1*10^{-3}$
t ,h, ad, nc, nb, rh, l	7-13-1	191	$3.58*10^{-3}$

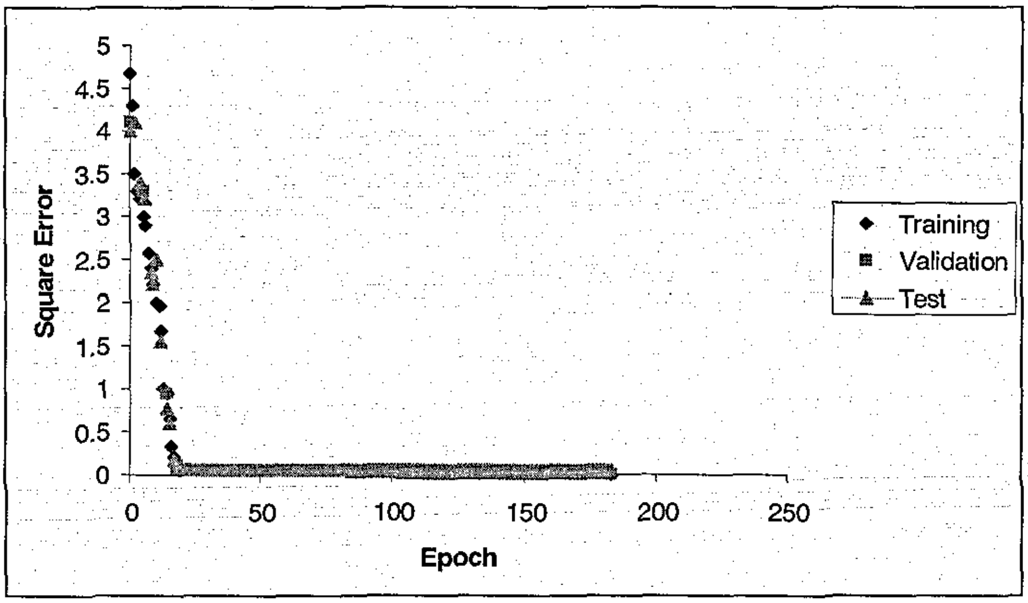


Figure 6.6: Performance of ANN during training

6.5.4 Simulation Results

The case study network was analysed for normal operations and also during a pipe failure event. The network analysis was performed using the conventional demand driven method,pressure dependendent demand method with Tabesh *et al.* (1997) function and the ANN based network analysis method developed in this thesis.

The consumer demand characteristics for the case study was assumed to follow those given in Chapter 2. The demand profiles for the nodes in the case study network were also developed as mentioned in Chapter 2.

The objective of analysing the case study network is to compare the different network analysis techniques and to determine the applicability of the ANN based network analysis method to the case study network.

It is expceted that all the three network analysis methods to produce similar results during the normal operation. However, when a failure event is introduced, the network behaviour is expected to differ from that of during normal operations.

In this section simulation results of of 25 nodes from the case study network are presented. Figures 6.7.1 a to 6.7.4 d show the results of 10 randomly selected noes. The remaining results are giveven in Appendix 3.

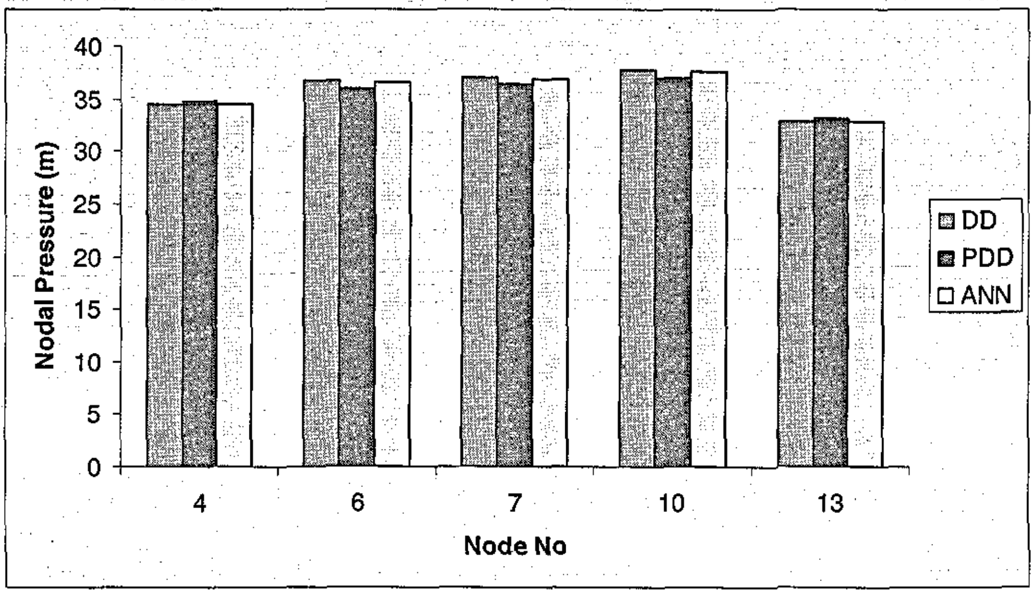


Figure 6.7.1a: Nodal Pressure during normal operation at 9 AM

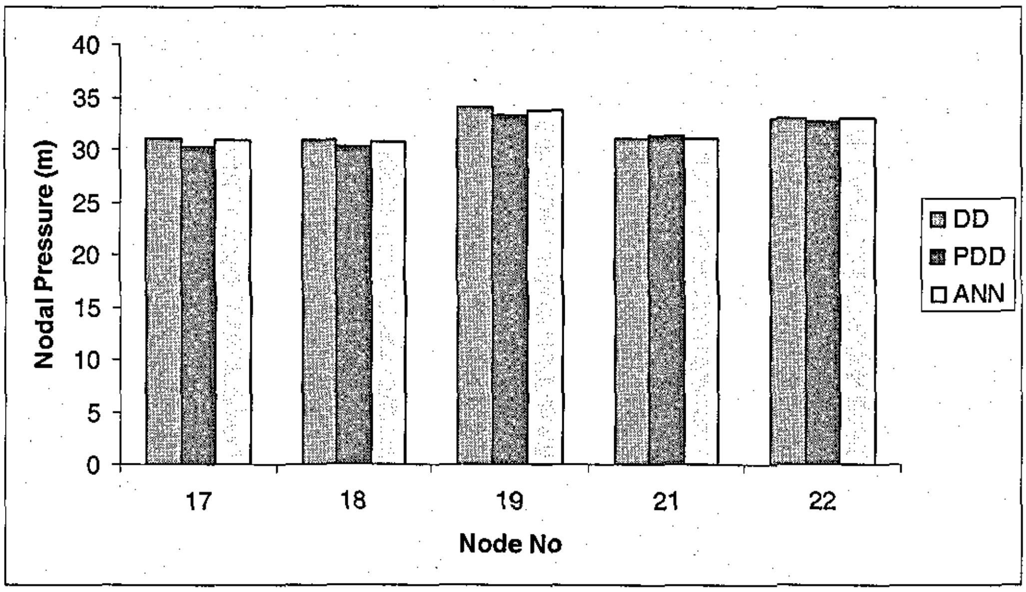


Figure 6.7.1b: Nodal Pressure during normal operation at 9 AM

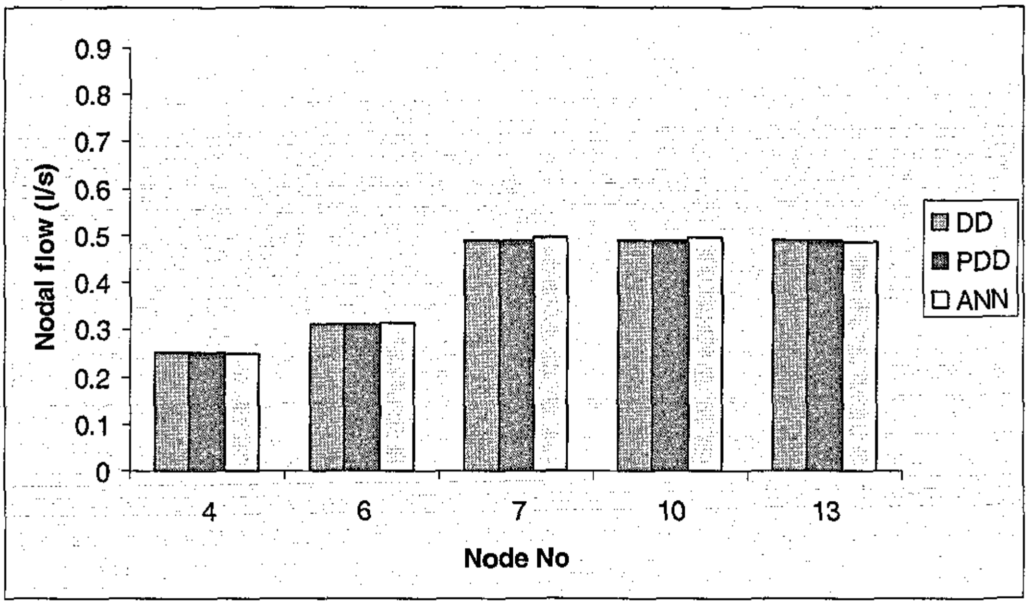


Figure 6.7.1c: Nodal flows during normal operation at 9 AM

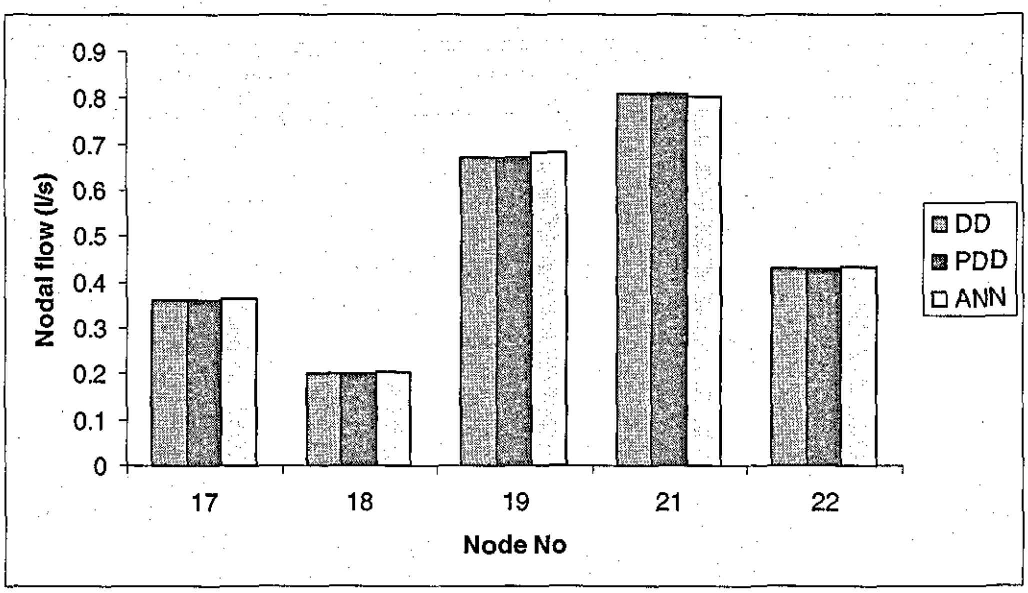


Figure 6.7.1d: Nodal flows during normal operation at 9 AM

Figures 6.7.1 a and 6.7.1 b shows the pressures at the nodes during the normal operation of the WDS at 9 am. The demand driven analysis, the PDD analysis and the ANN based analysis all produced very similar results.

The minimum and the desired pressure at nodes for the case study network were assumed to be 15m and 30m respectively. When the pressure at the nodes is above 30m, the network node receive the required demand at adequate pressure. All three types of analyses produced nodal pressures above 30m and their corresponding flows as shown in Figures 6.71 c and 6.71 d. The above figures suggest that the nodal outflows obtained using the DD,PDD and the ANN based methods are very similar.

Figures 6.7.2 a and 6.7.2 b, shown below indicate the pressure variation and the flow variation at nodes 6 and 22 during normal operations. Figure 6.7.2 a shows that there is a difference in pressure variations in the results obtained from the DD,PDD and the ANN based methods. However, the difference is very small and not significant enough to create big variations in the nodal outflows. Figures 6.7.2 c and 6.7.2 d show the flow variations at nodes 6 and 22 corresponding to the pressure variations shown in Figures 6.7.2 a and 6.7.2 b.

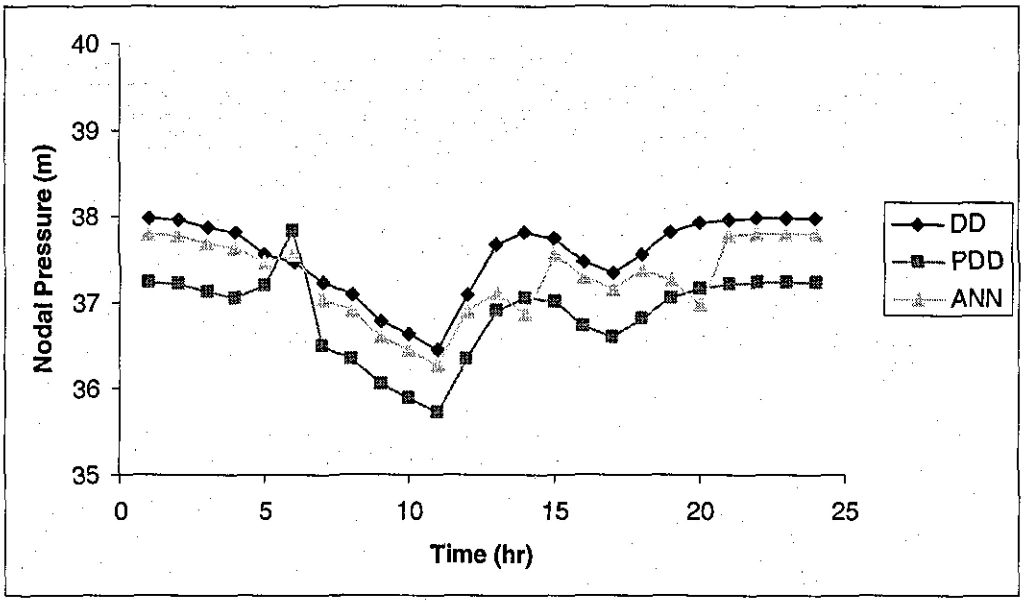


Figure 6.7.2 a: Pressure variation at node 6 during normal operation

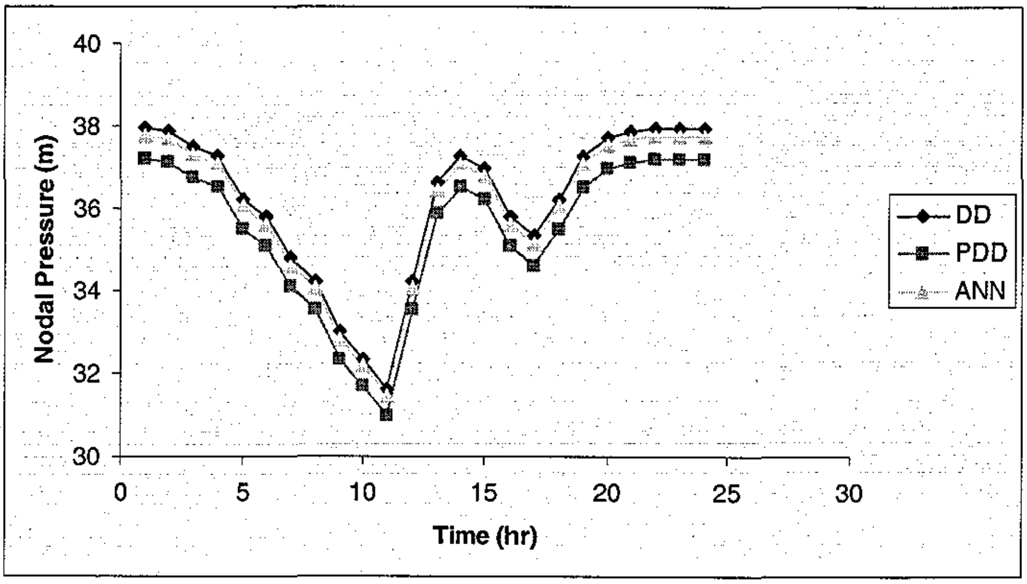


Figure 6.7.2 b: Pressure variation at node 22 at normal operation

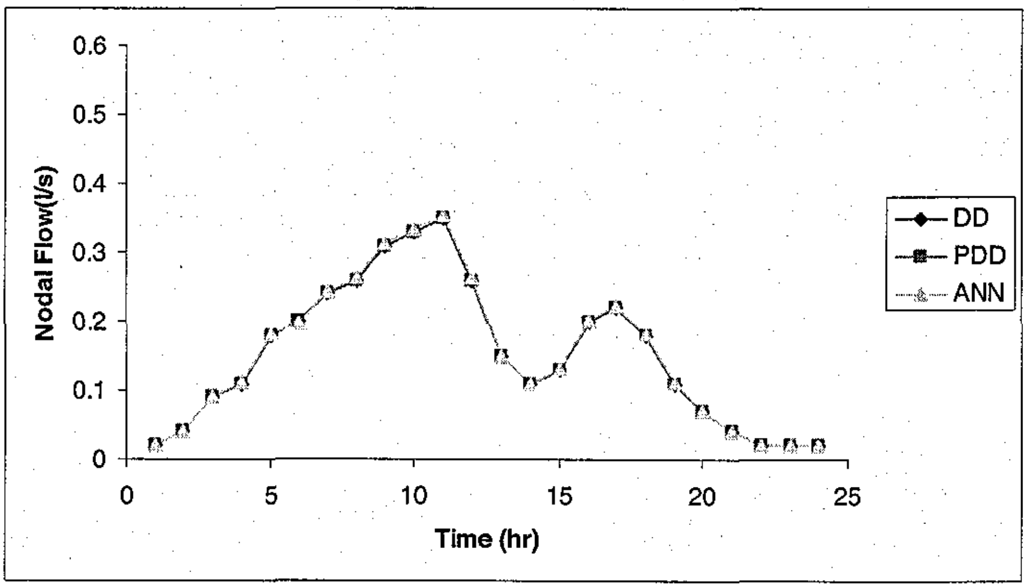


Figure 6.7.2 c: Flow variation at node 6 during normal operation

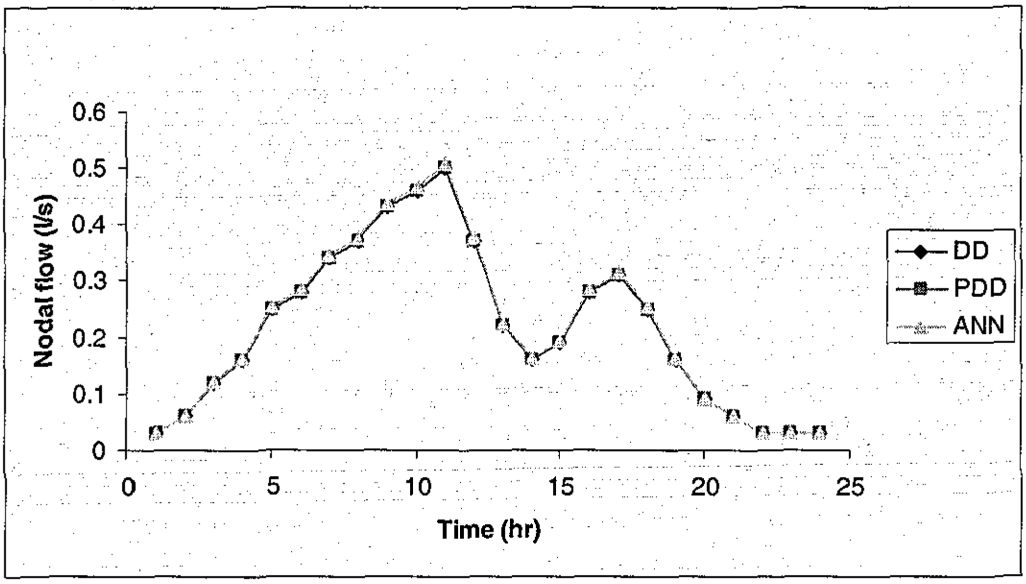


Figure 6.7.2 d: Flow variation at node 22 during normal operation

The flow variations obtained from the DD,PDD and the ANN methods at the nodes 6 and 22 show very little difference, which agrees with the difference in the variations of the pressure. These results indicate that, all the three methods of network analyses are applicable during normal operations.

It must be noted that, the DD method is not sensitive to pressure variations in the WDS like the other two methods. Therefore, during normal operations of the WDS, the network analysis method need not be sensitive to pressure variations.

The next step is to analyse the network when there is a failure event in the WDS. A pipe failure event was introduced on pipe 46 between the nodes 6 and 13. The failure event was represented as described in the section 6.3.

The failure event introduces pressure deficiency in the distribution system, as a result the nodal pressures are expected to fall. Figures 6.7.3 a and 6.7.3 b shows the pressure variations at the selected nodes during the failure event.

The pressure at nodes 4,6,7,10 and 13 have fallen from 34m, 36m, 37m, 37m and 32m to 16m, 9m, 19m , 35m and 0 during the failure event. There is a drastic drop in the pressures except at node 10.

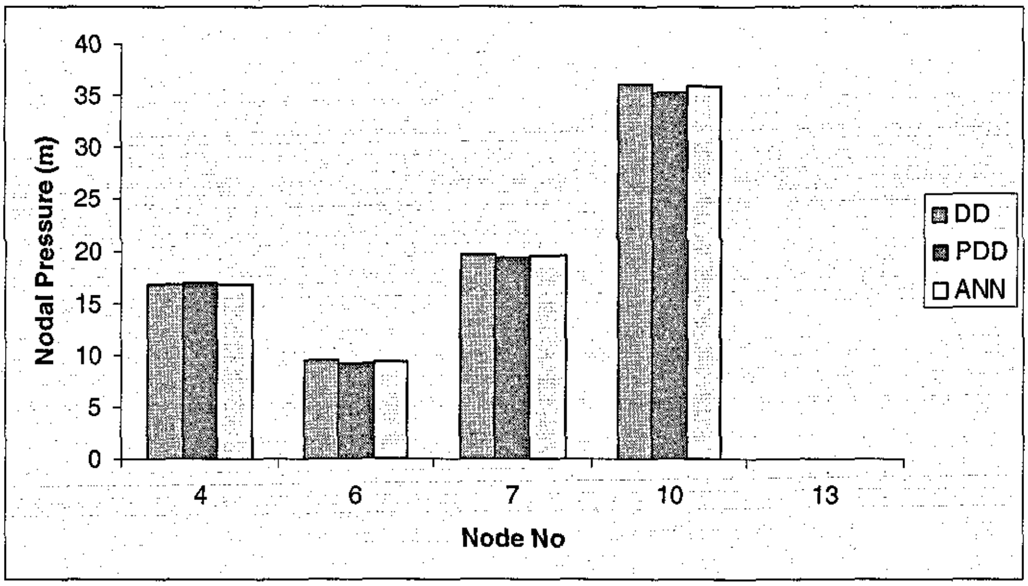


Figure 6.7.3a: Nodal Pressure during failure

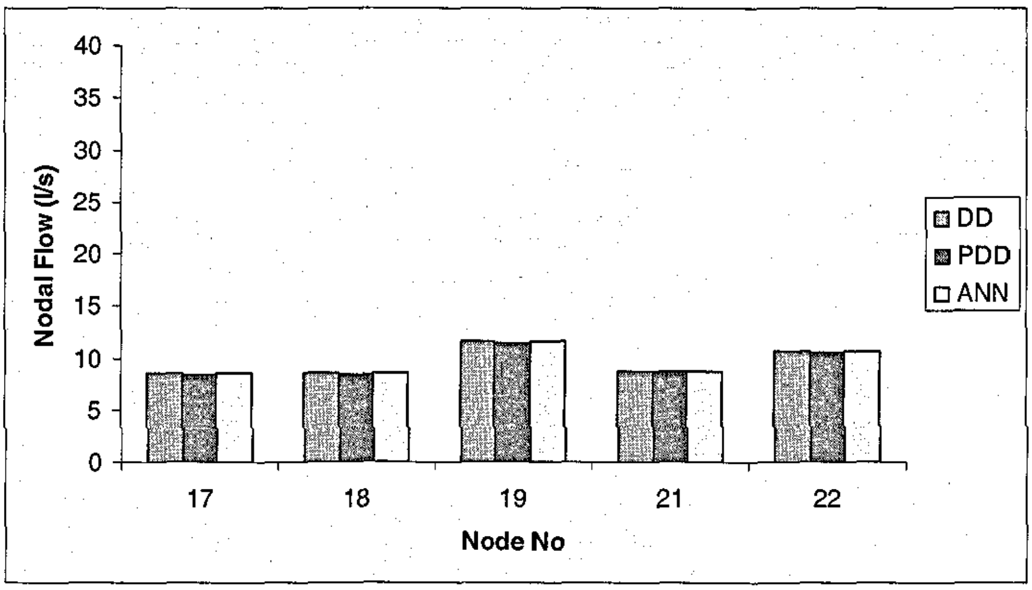


Figure 6.7.3b: Nodal Pressure during failure

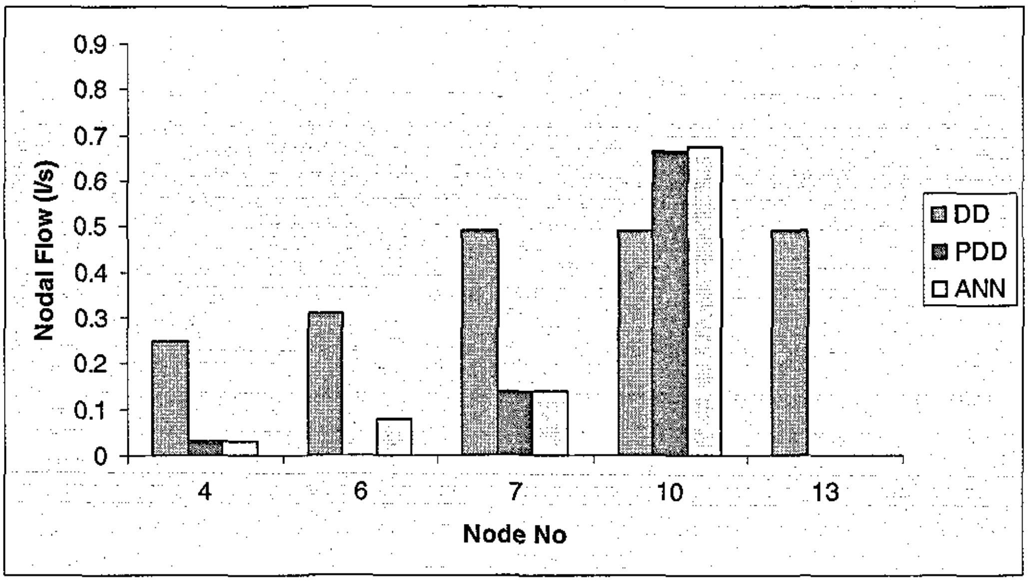


Figure 6.7.3c: Nodal Flows during failure

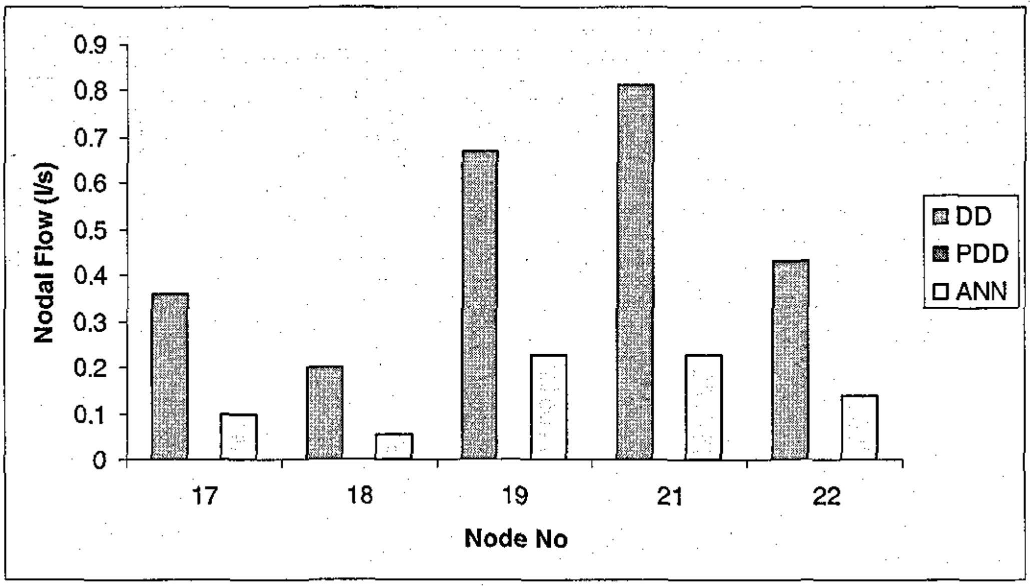


Figure 6.7.3d: Nodal Flows during failure

The nodal flows corresponding the nodal pressures are shown in Figures 6.7.3 c and 6.7.3 d. The nodal outflows obtained from DD analysis were same during normal operations and during the failure event. It is important to note that the DD method predicted 0 pressure at node 13 during the failure event, but the node still predicted an outflow. This is far from the reality. This behaviour is expected as the DD analysis is not sensitive to the pressure variations in the network.

Nodal outflows for the PDD and the ANN based analyses were lower than that of during normal operations thus indicating their sensitivity to pressure.

The pressures at node 6 for the PDD and ANN methods were 9.2m and 9.5m and their corresponding nodal outflows were 0 and 0.1l/s respectively during the failure event. The PDD analysis is not sensitive outside the minimum pressure and the desired pressure. Therefore, PDD analysis predicted a zero outflow for node 6. On the other hand the ANN based method does not have restrictions on the range of minimum and desired pressures and as a result predicts a nodal demand of 0.1l/s.

When the nodal pressure is between 15m and 30m for node 7, the DD, PDD and the ANN methods give pressures of 19.6 m, 19.2 m and 19.5 m respectively and the corresponding flows 0.49 l/s,0.13l/s and 0.14l/s. The PDD analysis and the ANN based analysis both predicted very similar demands for similar pressures. This suggestst that during a failure event both PDD analysis method and the ANN analysis method behave similarly when the available pressure is between the minimum and the desired pressures.

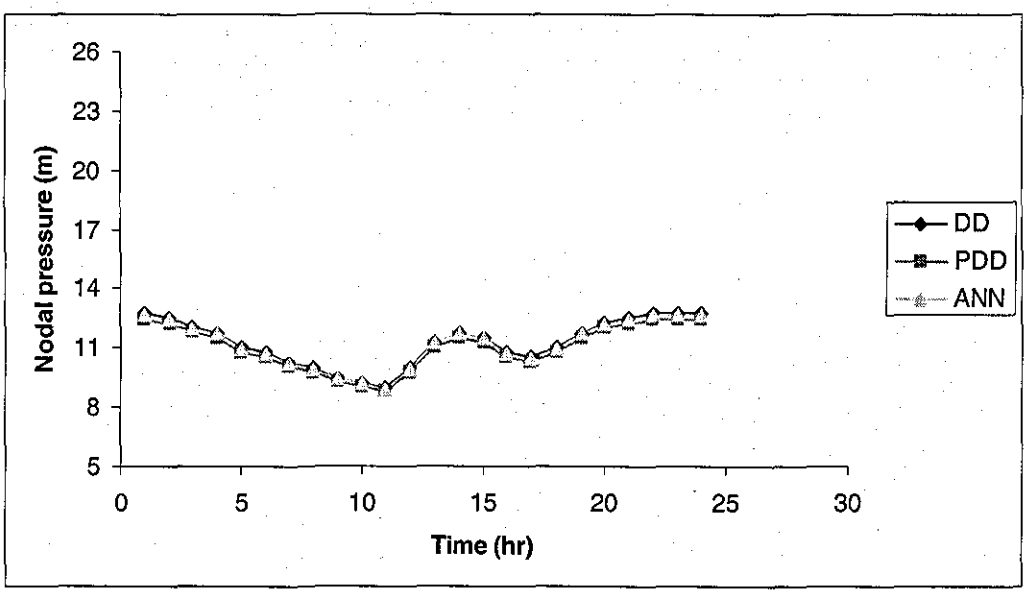


Figure 6.7.4a: Pressure Variation at node 6

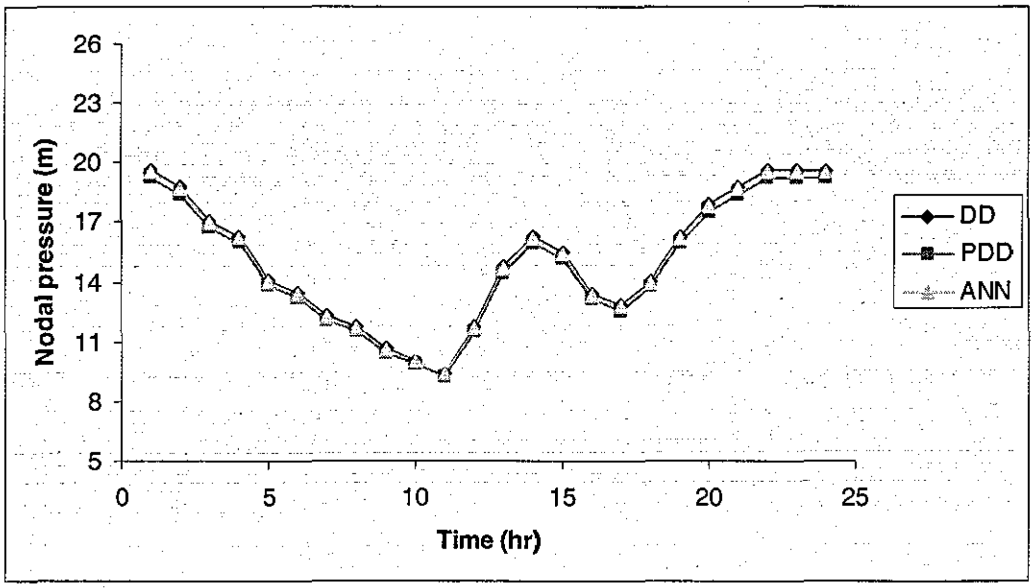


Figure 6.7.4b: Pressure Variation at node 22

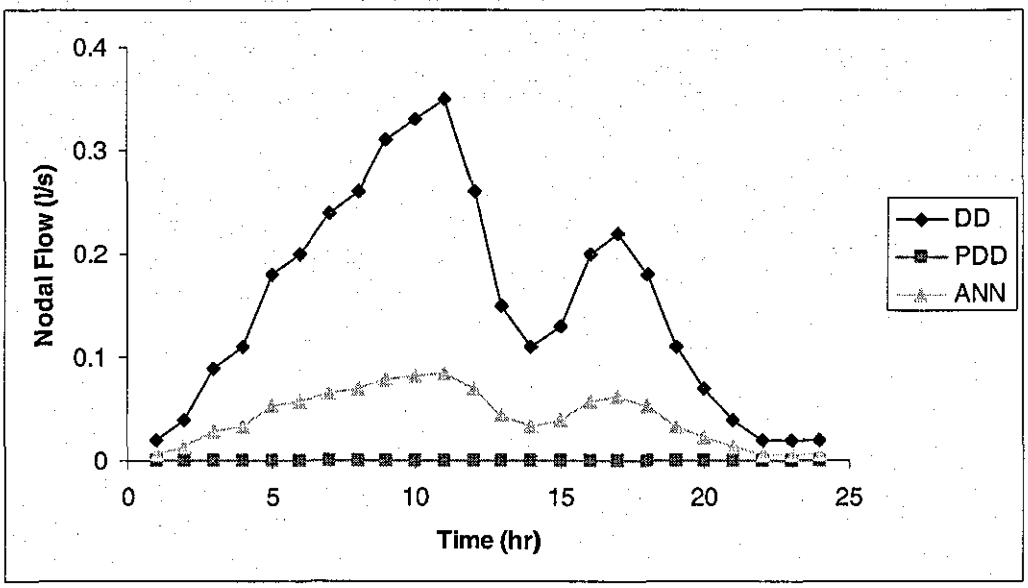


Figure 6.7.4c: Pressure Variation at node 6

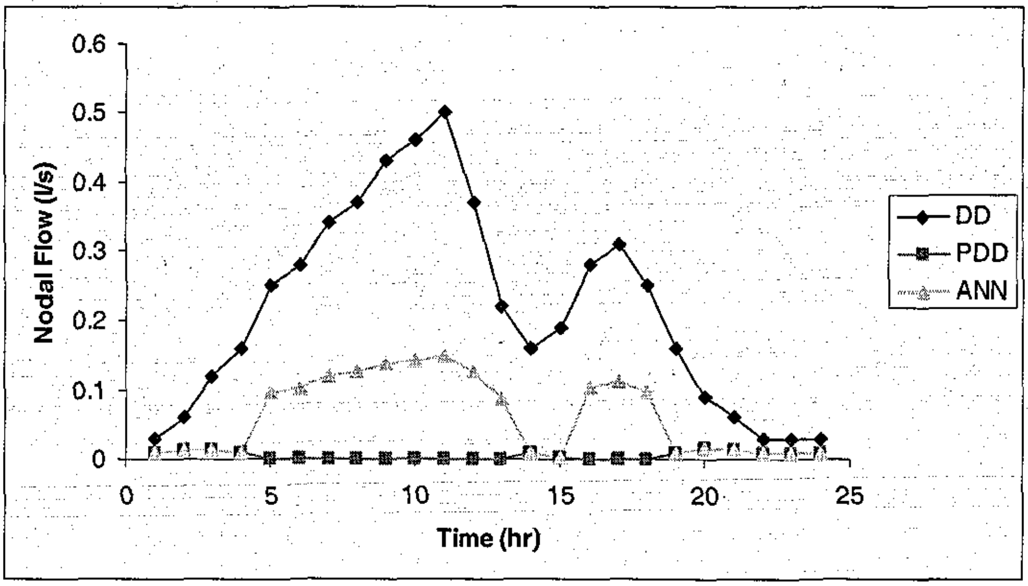


Figure 6.7.4d: Pressure Variation at node 22

By analysing the heads and the outflows at nodes 6 and 7, it can be concluded that the PDD analysis predicts pressure dependent nodal outflows when the available pressure is between the minimum and the desired preassures. On the other hand ANN based method is sensitive to pressure variations in the system regardless of the desired or minimum pressures.

Figures 6.7.4 a and 6.7.4 b show the pressure variations at the nodes 6 and 22 during the failure event for the three analysis methods. The difference between the pressure variations obtained from the DD, PDD and the ANN methods are very small at both the nodes. However, the corresponding flow variations are not similar as can be seen from Figures 6.7.4 c and 6.7.4 d.

The flow variation produced by the DD analysis for node 6 is the same as that obtained during the normal operations,but the PDD and the ANN methods differ. The PDD analysis method produced zero flow throughout the simulation period .This corresponds with the observations of the nodal pressure being below the minimum pressure range. The ANN based network analysis method produces a nodal flow throughout the simulation period. This shows that it does not depend on the minimum and desired pressures as discuused above. The results of node 7 can also be interpreted in a similar way.

6.5.5 Performance Measures

The results obtained from the network analysis program has been fed onto the performance assessment section which eveluates the performance measures as described in chapter 2. The performance measures evaluated using this model has been shown in Tables 6.4 and 6.5 below. In this section, results of only a few pipe failure events have been provided, The remaining results are given in the Appendix 3.

The performance of the nodes during failure events are identified using nodal adequacies, demand satisfaction ratios and severities. The nodal adequacies indicate the condition of the node after every failure event, whereas the demand satisfaction ratio identifies the performance throuougt the duration of the operation (10 years). The severity, on the other hand, expresses the failure experience of the consumers at the nodes.

For example, failure of pipe 1 results in almost all the nodes operating with a very low nodal adquacy in otherwords very low shortfalls in flow, infact majority of the nodes operate with zero demand shortfall. Therefore, the failure event does not cause a critical situation to the network.

Pipe 1 failure causes the node 1 to operate with an adequacy of 0.917, that is the node experiencing a demand loss of only 8.3% due to the failure event but the demand satisfaction ratio for node 1 is 0.967 indicating that 96.7% of the time node 1 is satisfies at least 90% of the required demand. These two performance measures demonstrate the behaviour of node 1 for individual and collective failure events in the WDS.

The severity at node 1 corresponding to pipe failure 1 is 0.027. This is obtained by taking account of the weighting factor at the node and the nodal adequacies. The nodal weights depend on the importance of the consumers and the consequences of the failure events. The severity thus expresses the experience of the consumers due to failures.

For a particular failure event nodes in the WDS have different severity values. For example the severity of the node 2 for pipe 1failure event is 0.016 which is lower than that of node 1. This suggests that the consumers at node 1 will experience more severe conditions than that at node 2. It is interesting to note that the nodal adequacies of node 1 is smaller (0.917) than that of node 2 (0.963), suggesting that node 2 have a lower demand short fall than node. This also conforms with the severity values. That is node 1has higher high importance and severe consequences than node2.

Table 6.4a: Nodal adequacies, node satisfaction ratio and equity for selected pipe failures

Pipe	1	2	4	6	8	10	13
Node	F1	F1	F1	F1	F1	F1	F1
1	0.917	0.343	0.319	0.454	0.634	0.583	0.650
2	0.963	0.307	0.352	0.459	0.652	0.571	0.650
3	0.981	0.292	0.364	0.459	0.652	0.571	0.637
4	1.000	0.239	0.408	0.547	0.722	0.667	0.744
5	0.915	0.340	0.326	0.423	0.602	0.533	0.601
6	1.000	0.263	0.381	0.459	0.573	0.595	0.664
7	1.000	0.278	0.370	0.466	0.640	0.572	0.650
8	1.000	0.225	0.422	0.500	0.675	0.508	0.697
9	1.000	0.069	0.565	0.667	0.824	0.639	0.837
10	1.000	0.250	0.404	0.519	0.692	0.606	0.621
11	1.000	0.150	0.484	0.612	0.784	0.686	0.724
12	1.000	0.000	0.785	0.950	1.000	0.948	1.000
13	0.985	0.289	0.366	0.465	0.632	0.574	0.640
14	0.875	0.369	0.302	0.399	0.576	0.514	0.573
15	0.983	0.291	0.367	0.477	0.641	0.583	0.638
16	1.000	0.184	0.444	0.547	0.711	0.658	0.716
17	1.000	0.230	0.424	0.523	0.692	0.621	0.693
18	1.000	0.056	0.568	0.677	0.812	0.763	0.823
19	0.986	0.289	0.370	0.461	0.645	0.574	0.640
20	0.915	0.340	0.326	0.423	0.594	0.533	0.588
21	0.929	0.330	0.336	0.441	0.610	0.548	0.603
23	0.929	0.332	0.327	0.443	0.625	0.557	0.621
24	0.875	0.369	0.294	0.400	0.582	0.514	0.579
25	1.000	0.051	0.561	0.664	0.803	0.765	0.855
26	0.937	0.324	0.339	0.445	0.614	0.560	0.625
27	1.000	0.264	0.387	0.467	0.662	0.594	0.677
28	1.000	0.263	0.391	0.504	0.679	0.609	0.678
29	0.936	0.325	0.340	0.428	0.623	0.553	0.617
30	0.932	0.327	0.335	0.423	0.604	0.483	0.598
31	0.926	0.332	0.331	0.419	0.599	0.489	0.601
32	0.937	0.324	0.339	0.435	0.614	0.487	0.609
33	0.944	0.318	0.336	0.431	0.608	0.477	0.604
34	1.000	0.262	0.402	0.495	0.661	0.484	0.664
35	0.943	0.319	0.338	0.431	0.606	0.474	0.603
36	1.000	0.220	0.420	0.540	0.720	0.630	0.674
37	1.000	0.071	0.548	0.686	0.857	0.750	0.786
39	1.000	0.206	0.439	0.560	0.733	0.642	0.592
40	0.985	0.289	0.366	0.453	0.632	0.564	0.640
41	1.000	0.253	0.391	0.507	0.690	0.603	0.648
42	1.000	0.184	0.462	0.568	0.751	0.658	0.679
43	0.918	0.337	0.324	0.422	0.597	0.535	0.596
44	0.983	0.291	0.370	0.466	0.626	0.572	0.638
45	0.920	0.336	0.327	0.423	0.595	0.536	0.598
48	1.000	0.234	0.412	0.512	0.674	0.618	0.690
49	0.922	0.334	0.328	0.426	0.602	0.537	0.599
50	1.000	0.266	0.379	0.479	0.649	0.592	0.648
51	1.000	0.267	0.387	0.487	0.663	0.592	0.660
52	1.000	0.179	0.454	0.556	0.735	0.662	0.739
53	1.000	0.085	0.543	0.646	0.812	0.763	0.823

Table 6.4b: Nodal adequacies, node satisfaction ratio and equity for selected pipe failures

Pipe	1	2	4	6	8	10	13
Node	**F1**	**F1**	**F1**	**F1**	**F1**	**F1**	**F1**
54	1.000	0.240	0.405	0.507	0.687	0.613	0.684
55	0.936	0.325	0.340	0.436	0.613	0.545	0.608
56	1.000	0.000	1.000	1.000	1.000	1.000	1.000
57	1.000	0.237	0.415	0.515	0.688	0.615	0.687
58	0.962	0.306	0.354	0.452	0.631	0.560	0.625
59	0.946	0.318	0.345	0.443	0.621	0.551	0.614
61	1.000	0.069	0.565	0.667	0.824	0.750	0.837
62	1.000	0.265	0.391	0.488	0.662	0.606	0.662
63	0.927	0.331	0.330	0.427	0.601	0.540	0.595
64	1.000	0.189	0.453	0.575	0.728	0.671	0.730
65	1.000	0.200	0.444	0.535	0.720	0.645	0.704
66	0.986	0.288	0.368	0.468	0.646	0.574	0.641
68	0.957	0.310	0.356	0.463	0.625	0.567	0.621
69	0.958	0.309	0.353	0.450	0.616	0.558	0.622
70	0.984	0.290	0.372	0.469	0.642	0.573	0.639
71	0.957	0.310	0.356	0.463	0.625	0.567	0.621
72	1.000	0.232	0.418	0.517	0.674	0.620	0.691
73	1.000	0.225	0.422	0.520	0.675	0.625	0.697
74	0.900	0.351	0.319	0.415	0.592	0.530	0.585
75	0.962	0.306	0.348	0.446	0.620	0.560	0.615
76	1.000	0.267	0.387	0.487	0.663	0.592	0.660
77	0.896	0.353	0.311	0.408	0.582	0.522	0.577
78	0.946	0.318	0.345	0.443	0.621	0.551	0.614
79	1.000	0.000	0.701	0.812	0.937	0.906	1.000
81	1.000	0.099	0.524	0.629	0.802	0.726	0.811
82	0.939	0.322	0.346	0.434	0.615	0.555	0.610
83	1.000	0.266	0.383	0.482	0.649	0.592	0.661
84	0.937	0.324	0.339	0.445	0.614	0.554	0.609
85	0.915	0.340	0.326	0.423	0.594	0.533	0.594
86	0.930	0.329	0.334	0.440	0.611	0.548	0.604
87	1.000	0.099	0.524	0.629	0.802	0.726	0.811
88	0.921	0.335	0.328	0.426	0.606	0.537	0.598
89	0.948	0.316	0.343	0.442	0.623	0.552	0.608
90	0.912	0.342	0.328	0.431	0.599	0.538	0.592
91	0.962	0.306	0.354	0.452	0.631	0.560	0.625
92	0.917	0.338	0.331	0.435	0.603	0.540	0.595
94	1.000	0.237	0.415	0.515	0.688	0.615	0.687
95	1.000	0.278	0.382	0.494	0.667	0.583	0.628
96	0.972	0.298	0.363	0.472	0.648	0.567	0.612
98	1.000	0.278	0.379	0.491	0.667	0.583	0.629
99	1.000	0.071	0.548	0.686	0.857	0.750	0.786
100	1.000	0.122	0.514	0.625	0.809	0.708	0.769
101	1.000	0.164	0.462	0.584	0.751	0.675	0.697
102	0.917	0.338	0.325	0.422	0.596	0.534	0.595
103	0.898	0.352	0.314	0.409	0.591	0.523	0.590
104	0.929	0.331	0.336	0.433	0.607	0.548	0.611
AD	0.968	0.257	0.402	0.504	0.673	0.600	0.667
Equity	0.962	0.900	0.824	0.828	0.572	0.681	0.580
$NSR_{90,}$	0.942	0.135	0.077	0.019	0.029	0.029	0.030

Table 6.5a: Nodal severities and demand satisfaction ratios

Pipe	1	2	4	6	8	10	$DSR_{90,I}$
Node							
1	0.027	0.217	0.225	0.180	0.121	0.138	0.967
2	0.016	0.291	0.272	0.227	0.146	0.180	0.989
3	0.006	0.234	0.210	0.179	0.115	0.142	0.956
4	0.000	0.320	0.249	0.190	0.117	0.140	0.856
5	0.036	0.277	0.283	0.242	0.167	0.196	0.978
6	0.000	0.273	0.229	0.200	0.158	0.150	0.9
7	0.000	0.379	0.331	0.280	0.189	0.225	0.744
8	0.000	0.256	0.191	0.165	0.107	0.162	0.922
9	0.000	0.307	0.144	0.110	0.058	0.119	0.867
10	0.000	0.315	0.250	0.202	0.129	0.165	0.911
11	0.000	0.281	0.170	0.128	0.071	0.104	0.711
12	0.000	0.443	0.095	0.022	0.000	0.023	0.756
13	0.005	0.235	0.209	0.177	0.121	0.141	0.822
14	0.041	0.208	0.230	0.198	0.140	0.160	0.678
15	0.006	0.234	0.209	0.173	0.118	0.138	0.844
16	0.000	0.269	0.183	0.149	0.095	0.113	0.956
17	0.000	0.254	0.190	0.157	0.102	0.125	0.889
18	0.000	0.312	0.143	0.107	0.062	0.078	0.878
19	0.005	0.235	0.208	0.178	0.117	0.141	0.744
20	0.028	0.218	0.222	0.190	0.134	0.154	0.9
21	0.023	0.221	0.219	0.184	0.129	0.149	0.789
23	0.023	0.220	0.222	0.184	0.124	0.146	0.689
24	0.041	0.208	0.233	0.198	0.138	0.160	0.778
25	0.000	0.399	0.184	0.141	0.083	0.099	0.856
26	0.026	0.284	0.278	0.233	0.162	0.185	0.956
27	0.000	0.243	0.202	0.176	0.112	0.134	0.8
28	0.000	0.327	0.270	0.220	0.142	0.173	0.967
29	0.021	0.223	0.218	0.189	0.124	0.148	0.833
30	0.029	0.283	0.279	0.242	0.166	0.217	0.922
31	0.024	0.220	0.221	0.192	0.132	0.169	0.856
32	0.028	0.300	0.293	0.250	0.171	0.227	0.922
33	0.018	0.225	0.219	0.188	0.129	0.173	0.822
34	0.000	0.244	0.197	0.167	0.112	0.170	0.711
35	0.028	0.334	0.324	0.279	0.193	0.258	0.889
36	0.000	0.328	0.244	0.193	0.118	0.155	0.7
37	0.000	0.307	0.149	0.104	0.047	0.083	0.856
39	0.000	0.262	0.185	0.145	0.088	0.118	0.822
40	0.005	0.235	0.209	0.181	0.121	0.144	0.789
41	0.000	0.247	0.201	0.163	0.102	0.131	0.933
42	0.000	0.343	0.226	0.181	0.105	0.144	0.9
43	0.027	0.219	0.223	0.191	0.133	0.153	0.744
44	0.006	0.234	0.208	0.176	0.123	0.141	0.8
45	0.032	0.269	0.273	0.234	0.164	0.188	0.967
48	0.000	0.340	0.261	0.216	0.145	0.169	0.933
49	0.033	0.280	0.282	0.241	0.167	0.194	0.789
50	0.000	0.242	0.205	0.172	0.116	0.135	0.767
51	0.000	0.242	0.202	0.169	0.111	0.135	0.778
52	0.000	0.271	0.180	0.147	0.087	0.112	0.744
53	0.000	0.302	0.151	0.117	0.062	0.078	0.944

Table 6.5b Nodal severities and demand satisfaction ratios

Pipe / Node	1	2	4	6	8	10	$DSR_{90,i}$
54	0.000	0.372	0.292	0.242	0.153	0.190	0.889
55	0.021	0.223	0.218	0.186	0.128	0.150	0.878
56	0.000	0.330	0.000	0.000	0.000	0.000	0.967
57	0.000	0.252	0.193	0.160	0.103	0.127	0.789
58	0.013	0.229	0.213	0.181	0.122	0.145	0.778
59	0.018	0.225	0.216	0.184	0.125	0.148	0.744
61	0.000	0.307	0.144	0.110	0.058	0.083	0.967
62	0.000	0.243	0.201	0.169	0.112	0.130	0.767
63	0.024	0.221	0.221	0.189	0.132	0.152	0.967
64	0.000	0.342	0.231	0.179	0.115	0.139	0.944
65	0.000	0.336	0.234	0.195	0.118	0.149	0.789
66	0.005	0.235	0.209	0.176	0.117	0.141	0.700
68	0.014	0.228	0.213	0.177	0.124	0.143	0.956
69	0.019	0.306	0.287	0.244	0.170	0.196	0.889
70	0.005	0.234	0.207	0.175	0.118	0.141	0.878
71	0.014	0.228	0.213	0.177	0.124	0.143	0.944
72	0.000	0.253	0.192	0.159	0.108	0.125	0.967
73	0.000	0.349	0.260	0.216	0.146	0.169	0.789
74	0.033	0.214	0.225	0.193	0.135	0.155	0.844
75	0.013	0.229	0.215	0.183	0.125	0.145	0.967
76	0.000	0.242	0.202	0.169	0.111	0.135	0.889
77	0.034	0.214	0.227	0.195	0.138	0.158	0.956
78	0.018	0.225	0.216	0.184	0.125	0.148	0.978
79	0.000	0.330	0.099	0.062	0.021	0.031	0.867
81	0.000	0.297	0.157	0.122	0.065	0.090	0.956
82	0.020	0.224	0.216	0.187	0.127	0.147	0.789
83	0.000	0.242	0.204	0.171	0.116	0.135	0.744
84	0.021	0.223	0.218	0.183	0.127	0.147	0.889
85	0.028	0.218	0.222	0.190	0.134	0.154	0.722
86	0.023	0.221	0.220	0.185	0.128	0.149	0.878
87	0.000	0.297	0.157	0.122	0.065	0.090	0.722
88	0.026	0.219	0.222	0.189	0.130	0.153	0.978
89	0.017	0.226	0.217	0.184	0.124	0.148	0.800
90	0.029	0.217	0.222	0.188	0.132	0.152	0.978
91	0.013	0.229	0.213	0.181	0.122	0.145	0.700
92	0.027	0.218	0.221	0.186	0.131	0.152	0.967
94	0.000	0.252	0.193	0.160	0.103	0.127	0.756
95	0.000	0.238	0.204	0.167	0.110	0.138	0.956
96	0.014	0.344	0.312	0.259	0.172	0.212	0.667
98	0.000	0.292	0.252	0.206	0.135	0.169	0.956
99	0.000	0.307	0.149	0.104	0.047	0.083	0.878
100	0.000	0.290	0.160	0.124	0.063	0.096	0.967
101	0.000	0.276	0.178	0.137	0.082	0.107	0.856
102	0.027	0.218	0.223	0.191	0.133	0.154	0.711
103	0.034	0.214	0.226	0.195	0.135	0.157	0.878
104	0.023	0.221	0.219	0.187	0.130	0.149	0.967

It is also important to note that of severities at nodes only indicate the relative experiences of the consumers at nodes. The higher the value of the severity measure the more severe the failure experience of the consumer.

The behaviour of a WDS during a failure event is driven by the collective performances of the nodes. There are numerous methods of representing the collective nodal performance which have been discussed in chapter 2. Measures that are employed to determine the WDS performance are equity, system adequacy and node satisfaction ratio.

Equity referes to uniformity of supply to consumers or nodes. This measure tries to quantify the uniformity in the reduced flows to the nodes during faiulures in the WDS. For example equity among the nodes during failures of pipes 1 and 4 are 0.962, 0.824 respectively, whereas the system adequacies for the same failures are 0.968, 0.402 respectively. Comparing the equities along with system adequacies reveal that, higher the system adequacy, the higher the value of equity, indicating that when there is a larger quantity of water, the uniformity in supply will be high. The above values of equity suggest that pipe 1 failure result in a more equitable supply to the nodes than that during pipe 4 failure. It can also be seen that high adequacy for pipe 1 failure has higher equity and a lower adequacy for pipe 4 failure also has higher value of equity. This suggests that although the amount of water received by nodes is lower during the pipe 4 failure, the supply among the nodes has high uniformity. The reason behind this is the uniformity in pressure among the nodes after the failure events.

It is not essential that higher adequacy values should always have higher equities, there may be situations where a failure event results in a high value of adequacy and a low value of equity. This will be a result of the location of the failure and the pressure distribution in the WDS which causes the non uniformity in the distribution of flow among the nodes, therefore causing a low equity.

When equity equals unity, all the nodes will receive a uniform supply that is proportional to their demands, in other words nodes receive an equitable supply.

The node satisfaction ratio expresses that the percentage of nodes operating with at least a pre specified demand. In this case, 90% of demand for a failure event. The node satisfaction ratios for the failures of pipes 1 and 4 are 0.942 and 0.077. That is 94.2% of the nodes and 7.7% of the nodes operates at least with 90% of the demand during failures of pipes 1 and 4 respectively. In other words the only 5.8% of the node and 92.3% of the nodes will be operating below 90% of demand during the two failures. The adequacy values for the failures of pipe 1 and 4 correspond with the values obtained for node satisfaction ratios.

Therefore, the performance measures that describe the system performance complement each other and also they indicate different aspects of the performance of the system during failure.

6.6 Conclusion

This chapter describes the integration of the different components that constitute the performance assessment model developed in this thesis.

Individual components (the failure prediction model, network analysis and the performance measures) of the model have been comprehensively discussed in the earlier chapters. The failure prediction model generates probable component failure events in the WDS. The ANN based network analysis simulates the behaviour of the water distribution network. Performance measures quantify the characteristics of the water distribution network and consumer's failure experiences during the operation of the WDS.

The three separate components of the performance assessment model need to communicate with each other in order to predict the performance of the WDS. Component failures are obtained from the failure prediction model. The failure events are represented in the network analysis model and the ANN based network analysis is used to simulate the failed water distribution network. The nodal pressures and the outflows are transferred to the performance measures to determine the WDS performance.

The performance assessment model developed in this thesis is applied to a case study system to demonstrate the applicability of the model. The case study network is located in the greater Birmingham area which comes under the Severn Trent water utility. Therefore, the average Severn Trent per capita consumptions were used to generate the consumer demands.

The network analysis simulations of the case study network, showed that the ANN based network analysis component of the performance assessment model is applicable to a WDS operating under the normal conditions as well as well as the pressure deficient conditions. Furthermore, it was shown that the ANN based model was more appropriate than the PDD approach as the ANN based method does not depend on the minimum and desired nodal pressures as opposed to the PDD approach based on the pressure dependent demand functions.

The outputs of the network analysis program were used to demonstrate the applicability of the performance measures to the case study network.

It was shown that the performance measures proposed in this thesis were able to expose different characteristics of the WDS behaviour. Especially the equitable distribution of water among the consumers, adequacies of the water supply and the consumers' failure experiences.

The principal conclusions of this chapter are:

- The performance assessment model developed in this thesis can be applied to real water distribution systems.

- The network analysis model depends on the secondary network information.

- The performance measures demonstrate different aspects of the behaviour of the WDS during failure events.

CHAPTER 7

CONCLUSION

7.1 General Conclusions

This thesis has investigated the issues in the existing methods of performance assessment of water distribution systems and shown that there is a need to improve the hydraulic network analysis for properly assessing the performance measures.

In order to assess the performance of water distribution systems, the thesis has recognised that the usual demand driven approach is not suitable to assess the performance measures. During the events of failure of WDS, the demands are pressure dependent and hence it is important to recognise the pressure dependent nature of demand during network analysis and devise the appropriate performance measures.

The shortcomings associated with the existing pressure dependent demand analysis were investigated. It was found that the PDD analysis method that is capable of representing the secondary network behaviour is more appropriate for the simulation of pressure dependent demands of WDS during failure events. A significant achievement of this research is the development of PDD analysis based on the micro level models that represent the secondary network behaviour appropriately. Another achievement of this thesis is the development of technique based on artificial neural networks to represent the behaviour of secondary networks. These ANNs are incorporated with the network analysis program by way of numerical methods. This simplified the application of micro level methods.

The performance assessment procedure consists of predicting and representing failure events in the WDS, simulating the network conditions using network analysis and assessing the performance with the proposed performance measures.

7.2 Specific Conclusion

7.2.1 Modified PDD analysis

This thesis has shown that the major modification required to the network analysis process is in how the pressure dependent nodal outflows are evaluated. It was shown that the demand driven approach that is conventionally used to evaluate nodal demands is not appropriate in predicting nodal out flows when the WDS experience deficient system pressure. This is because extreme events in WDS cause high head losses and also loss in carrying capacity thus creating a pressure deficient situation in the distribution system. Therefore, currently available methods use PDD functions incorporated with network analysis to address this issue. The role of the PDD function is to predict the pressure dependent outflows in the water network as a result of the changes in the secondary networks. However, PDD functions do not represent secondary networks behaviour in the WDS and hence it is not possible to appropriately assess the performance of WDS with the help of existing PDD functions, especially in the events of failure of WDS.

In this thesis an alternative method to PDD function is therefore, presented which is based on representing the secondary network behaviour. Therefore, this method is more appropriate than the PDD functions.

The proposed method of network analysis is basically a method that incorporates the secondary networks of corresponding primary nodes in the WDS and incorporates the detailed information of the secondary network including the consumers' piping arrangements into the analysis.

However it is not practical to incorporate details of each and every individual consumer and hence behaviours of homogeneous consumers are lumped using Voronoi Polygons so that secondary networks are simplified. It is also not practical for large networks to have secondary networks attached to each primary node due to the complexity involved in the modelling. Therefore, ANN has been used to represent the secondary network behaviours of WDS. The ANN is trained with the features of secondary networks and incorporated with the network analysis. This new method is basically a micro level analysis but without physically incorporating the secondary networks.

This modified method of representing secondary network by trained ANNs has been applied to example networks and compared with the existing PDD functions. The modified method predicts comparable results and these results are more appropriate as they incorporate the actual secondary network behaviour in the WDS unlike the PDD functions.

7.2.2 Performance measures

The second aspect of the performance assessment of WDS is the use of appropriate performance measures. In this thesis new performance measures were introduced that can be used to identify the various states in the WDS due to failure events. The proposed performance measures mainly identify the actual state of the nodes as well as the system; unlike the existing reliability and risk-based measures. The proposed measures can be used to evaluate the actual states of nodes in terms of supply with respect to demand as a result of failure events. Furthermore these measures are capable of identifying the distribution of supply among the nodes of the network during extreme events and hence reflect the equity in supply to the consumers. During a normal operation all nodes will get their required share of supply and hence the equity is unity. However, a failure event may result in highly inequitable situation in the distribution system. Here equity does not merely suggest the equal quantities of water that is supplied to the nodes; instead the equity is described for demand satisfaction ratios.

Another feature of the proposed performance measure is that they assist in understanding the experience of different stakeholders such as water users (consumers), water industries and utilities and water boards (council) during the events of failure. This is very important, as primarily a failure event in WDS will have direct impact on these stakeholders. Then again the importance of different water users or consumers and the consequence of inadequate water supply may vary depending on the characteristics of the consumers and the adequacy of supplies to the consumers. This has been incorporated through a factor called weighted factor for each node. The importance of the consumers and consequences of failure of water supply are derived using weightings obtained from consumer surveys and the importance of different stakeholders could be obtained by AHP.

Overall the proposed performance measures are useful to investigate the behaviour of the WDS due to extreme events. To assess the performance of WDS using the proposed performance measures, the hydraulic analysis of the network needs to be carried out using the proposed micro-level method that incorporates ANNs. It should be noted here that the existing reliability based performance measures combined with the proposed hydraulic analysis will also provide a useful tool for performance assessments of WDS.

7.2.3 Simulation

The performance assessment methodology consists of three procedures, namely: component failure prediction model, hydraulic network analysis and performance measures. This thesis is mainly concerned with the latter two procedures and accordingly developed the new procedure for hydraulic network analysis and produced the new set of performance measures. The failure prediction model simulates the random component failure behaviour. In the present study, the simulation model proposed by Wagner *et al.,* (1988b) is used with slight modifications to incorporate the durations of failures (failure and repair durations). It is very important to note that the simulation method introduced in this thesis takes into account the various states of failures including dynamic failure state (immediately after failure) and the reduced state (where the failed components are isolated for repair) in which the network operates with a reduced carrying capacity. The three models are combined to produce the performance assessment model.

7.3 Future Research

The results of this research expose some issues and potential areas for further investigations.

- The failure prediction model proposed in this thesis considers random failure behaviour of the components by using a Monte Carlo method. This also can be studied by considering the failure histories of the components by incorporating prior probabilities and posterior probabilities using Bayesian probability techniques. This method would produce improved failure predictions of the components.

- The proposed network analysis model is based on secondary networks. The analysis method considers the entire network during failure events. An alternative method may be to identify the areas of influence of failures in the WDS and extract that particular area for the analysis, rather than performing the simulation for the entire network. This approach would help to analyse the parts of the failed networks in greater detail.

- To mimic the secondary network behaviours of WDS, ANNs were used. In this thesis only multi layer perceptron networks (MLP) were used. However, instead of using static feed forward networks like MLPs, use of dynamic networks (recurrent networks) which have inbuilt time delay components can also be explored.

- Performance measures proposed in this thesis primarily describe the consequences of failure in the WDS and also the failure experience of different stakeholders. The measure that describes the failure experience is derived based only on adequacy, however the failure experience can be further refined by incorporating other measures such as equity and demand satisfaction ratios for example using an analytical hierarchy process.

7.4 End Point

This thesis has made contributions to understanding of how water distribution systems behave during failure events and how they should be analysed and their performance evaluated. The proposed network analysis model represents realistic situations in the WDS and the new performance measures contribute to the detailed understanding of the WDS behaviour.

It is emphasised that the ANN based network analysis technique proposed in this thesis is a step forward in analysing deficient WDS. Also introduction of performance measures that evaluate the consumers' failure experience is the first step in devising new and more comprehensive measures. It is anticipated that future research will result in better understanding of the performance of WDS.

REFERENCES

Abebe, A. J., and Price, R. K., (2004). "Forecasting Surge Prediction Accuracy on the Dutch Coast using Neural Networks. " *Proceedings of International conference on Hydro Informatics Singapore- 2004.*, 1409-1416.

Abebe, A. J., Solomatine, D.P., and Venneker, R. G.W., (2000). "Application of Adaptive Fuzzy Rule-Based Models for Reconstruction of Missing Precipitation Events". *Hydrological Sci-Journal-des Sciences Hydrologiques.* , 45 (3) 425-436.

Ahamed, M., and Melchers, R. E., (1994). "Reliability of underground pipelines subjected to corrosion." *Journal of Transportation Engineering, ASCE*, 120(6), 989-1003.

Ahamed, M., and Melchers, R. E., (1995). "Probabilistic analysis of pipelines subjected to piting corrosion leaks." *Engineering Structures.*, 17(2) 74-80.

Akinpelu, E. O., (2001). *Development of Appropriate Demand Modeling Procedure for Water Distribution Systems in Developing Countries.* Thesis Presented to the South Bank University, at London, UK in partial fulfillment of the requirement for the degree of Doctor of Philosophy.

Alegre, H., (1992). *Decision Support Tools for Technical Management of Water Distribution Systems.* PhD Thesis Volume 1 of the Series Thesis and Research Programs, LNEC, Lisbon, Portugal, 284-290 (in Portugese).

Almasri, M.N., and Kaluarachchi, J.J., (2004). "Modular Neural Networks to Predict the Nitrate Distribution in Ground Water Using the On-Ground Nitrogen Loading and Recharge Data"., *Environmental Modeling and Software.*,

Alvisi, S., Franchini, M., and Marinelli, A., (2003). "A Stochastic Model for Representing Drinking Water Demand at Residential Level". *Water Resources Research.*, 197-222.

Al-Zaharani, M., and Syed, J.L., (2004). "Hydraulic Reliability Analysis of Water Distribution System". *Journal of the Institution of Engineers, Singapore.*, 1 76-92.

An, A., Shan, N., Chan, C., Cercone, C., and Ziarko, W., (1996). "Discovering Rules for Water Demand Prediction: An Enhanced Rough-Set Approach". *Pergamon.* 9 (6) 645-653.

Anctil, F., and Tape, D.G., (2004). "AN Exploration of artificial neural network rainfall- run off forecasting combined with wavelet decomposition" Journal of Environmental Engineering Science. (3) 121-128.

Anderson, E. J., and Al-Jamal, K.H., (1995). "Hydraulic-Network Simplification". *Journal of Water Resources Planning and Management.*, 121 (3) 235-240.

Andreou, S. A., Marks, D. H., and Clark, R. M., (1987a). "A new methodology for modelling break failure patterns in deteriorating water distribution system: Theory." *Advance in Water Resources*, 10 (2-10).

Andreou, S. A., Marks, D. H., and Clark, R. M., (1987b). "A new methodology for modelling break failure patterns in deteriorating water distribution systems: Applications." *Advance in Water Resources*, 10(11-20).

Ang, A. H., and Tang, W. H., (1984). *Probability concepts in engineering planning and design*, Willey, New York.

AWWARF. (1989). " Economics of Internal Corrosion Control."

AWWARF/DVGW. (1986). "Internal Corrosion of Water Distribution Systems."

AWWSC. (2002). "Deteriorating buried infrastructure management challenges and strategies." White Paper Prepared for US Environmental Protection Agency workshop on Distribution System Issues, March 7-8, Voorhees, NJ.

Axworthy, D.H., and Karney, B.W., (1996). "Filling of Pipelines With Undulating Elevation Profiles". *Journal of Hydraulic Engineering* ., 122 (10) 1170-1175.

Bailey, R.J., Jolly, P.K., and Lacey, R.F., (1986) "Domestic Water Use Patterns". *WRC Technical Report TR 225*, Stevenage Laboratory.

Bao, Y., and Mays, L.W., (1990). "Hydraulic Reliability Analysis of Water Distribution Systems". *Journal of Hydraulic Engineering (ASCE).*, 116 (9) 1119-1138.

Bao, Y., and Mays, L.W., (1989). "Model for Water Distribution System Reliability". *Journal of Hydraulic Engineering (ASCE).*, 116 (9) 1119-1133.

Bardossy, A., and Duckstein, L., (1992). "Analysis of a karstic aquifer management problem by fuzzy composite programming." *Water Resources Bulletin*, 28(1) 63-73.

Bargiela, A., and Hainswort, G.D., (1987). "Pressure and Flow Uncertainty in Water Systems"., 115 (2) 212-229.

Bennis, S., Bengassem, J., and Lamarre, P., (2000). "Hydraulic Performance Index of a Sewer Network". *Journal of Hydraulic Engineering.*, 129 (7) 504-510.

Bhave, P.R., (1996). "Calibrating Water Distribution Network Models". *Journal of Environmental Engineering.*, 114 (1) 120-136.

Bhave, P.R., (1988). "Extended Period Simulation of Water Systems-Direct Solution". *Journal of Environmental Engineering (ASCE).* , 114 (5) 1146-1159.

Bhave, P.R., (1980). "Node Flow Analysis of Water Distribution Systems".*Journal of Transportation Engineering (ASCE).*, 107 (TE4) 457-467.

Bishop, C. M,. (1995). *Neural Networks for Pattern Recognition.* 1st edition, Oxford University Press (ISBN 0-19-853849-9).

Bos, M. G., Murray-Rust, D. H., Merrey, D. J., Johnson, H. G., and Snellen, W. B., (1994). "Methodologies for assessing performance of irrigation and drainage management." Irrigation and drainage systems, 7, 231-261.

Bouchart, F., and Goulter, I., (1992). "Selecting Valve Location to Optimise Water Distribution Network Reliability". *Journal of Environmental Engineering (ASCE).* , 155-162.

Bouchart, F., and Goulter, I.C., (1988). "Reliability Improvements in Design of Water Distribution Networks Recognizing Valve Location". *Water Resources Research.,* 27 (12) 3029-3041.

Buchberger, S.G., and Wells, G. J., (1996). "Intensity, Duration, and Frequency of Residential Water Demands". *Journal of Water Resources Planning and Management (ASCE).,* 122 (1) 11-19.

Buchberger, S,G., and Wu, L., (1993). "Model for Instantaneous Residential Water Demands". *Journal of Hydraulic Engineering (ASCE).,* 121 (3) 232-246.

Bu Hamra, S., Smaoui, N., and Gabr, M., (2003). "The Box-Jenkins and Neural Networks: Prediction and Time Series Modeling". *Applied Mathematical Modelling.,* 27 805-815.

Cerda-Villafana, G., Cluckie, I,D., and Han, D., (2004) "An Approaches on Evaluating the Pre-Processing of Rainfall and Runoff Data in Artificial Neural Network Modeling for Real-Time Forecasting. *Proceedings of International conference on Hydro Informatics Singapore-2004.,* 1345-1352.

Chandapillai, J., (1991). "Realistic Simulation of Water Distribution System". *Journal of Transportation Engineering.,* 117 (2) 258-263.

Clark, R, C., Sivaganesan, M., Selvakumar, A., and Sethi, V., (2000). "Cost Models for Water Supply Distribution Systems". *Journal of Water Resources Planning and Management.,* 128 (5) 312-321.

Clark, R. M., Stafford, C. L., and Goodrich, J. A., (1982). "Water distribution system: A spatial and cost evaluation." Journal of Water Resources Planning and Management, ASCE, 108(3) 243-256.

Constantine, A. G., and Darroch, J. N., (1993). "Stochastic model in engineering technology and management." Pipeline reliability, S. Osaki and D. N. P. Murthy, eds., World Scientific, Singapore.

Cooper, N.R., Blakey, G., Sherwin, Ta, T., Whiter, J.T., and Woodward, C. A., (2000). "The Use of GIS to Develop a Probability-Based Trunk Mains Burst Risk Model". *Urban Water .,* 2 97-103.

Cowperwait, P.S.P., O' Connell, P.E.O., Metcalfe, A.V., and Mawdsley, J.A., (1996a). "Stochastic Point Process Modelling of Rainfall, I.Single-Site fitting Validation". *Journal of Hydrology (ASCE).,* 175, 17-46.

Cowperwait, P.S.P., O' Connell, P.E.O., Metcalfe, A.V., and Mawdsley, J.A., (1996a). "Stochastic Point Process Modelling of Rainfall, II. Regionalisation and Disaggregating". *Journal of Hydrology (ASCE).,* 175, 47-65.

Cox, D. R., (1972). "Regression models and life tables." *Journal of Royal Statistic Society,* 34(B), 187-220.

Cullinane, M.J., Lansey, K.E., and Mays, L.W., (1992). "Optimization-Availability-Based Design of Water-Distribution Networks". *Journal of Hydraulic Engineering (ASCE).,* 118 (3) 420-441.

Cunat, P.J., (2001). "Corrosion Resistance of Stainless Steels in Soils and in Concrete." Paper presented at the Plenary Days of the Committee on the Study of Pipe Corrossion and Protection, October 2001, Ceocor, Biarritz.

Dae Sung Lee and Jong Moon Park (1999). "Neural Network Modeling for online Estimation of Nutrient Dynamics in a Sequentially Operated Batch Reactor". *Journal of Bio Technology*, 75 229-239.

Davies, J. P., Clarke, B. A., Whiter, J. T., and Cunningham, R. J., (2001). "Factors influencing the structural deterioration and collapse of rigid sewer pipes." Urban Water, 3(1-2) 73-89.

Deb, A. K., Hasit, Y., Grablutz, J. F. M., and Herz, R. K., (1998). "Quantifying future rehabilitation and replacement needs of water mains." AWWA Research Foundation, Denver, Colo.

Doleac, M. L., (1979). "Time-to failure analysis of cast iron water mains." *Report submitted to the City of Vancouver by CH2M HILL, BC, Canada.*

Doleac, M. L., Lackey, S. L., and Bratton, G. N., (1980) "Prediction of time-to failure for buried cast iron pipe." *Proceeding of American water works association annual conference, pp. 21-28.*, Denver, CO.

Dibike, Y,B., Velickov, S., Solomatine, D.P., and Abbott, M.B., (2000). "Model Induction with Support Vector Machines: Introduction and Applications". *Journal of computing in Civil Engineering.*, 15 (3) 208-216.

Duan, N., and Mays, L.W., (1988). "Reliability Analysis of Pumping Systems". *Journal of Hydraulic Engineering (ASCE).*, 116 (2) 230-248.

Duan, N., Mays, L.W., and Lansey, K.E., (1988). "Optimal Reliability-Based Design of Pumping and Distribution Systems". *Journal of Hydraulic Engineering (ASCE).*, 116 (2) 249-268.

Eisenbeis, P., Rostum, J., and Le Gat, Y., (1999). "Statistical models for assessing the technical state of water networks - some European experiences." *Proceeding of the AWWA Annual Conference, Chicago.*

Elman, J., L., (1991) "Distributed representations, simple recurrent networks, and grammatical structure" Journal of Machine Learning Springer Publishers, The Netherlands.7 (4) 195-225.

Engelhardt, M.O., Skipworth, P.J., Savic, D.A., Sual, A.J., and Walters, G.A., (2000). "Rehabilitation Strategies for Water Distribution Networks: A Literature Review with a UK Perspective".*Urban Water,* 153-170.

Ezell, B.C., Farr, J.V., and Wiese, I., (1999). "Infrastructure Risk Analysis of Municipal Water Distribution System". *Journal of Infrastructure Systems.*, 6 (3) 118-122.

Farley, M., and Trow, S., (2001). "Losses in Water Distribution Networks: A Practitioner's Guide to Assessment, Monitoring and Control." *IWA Publishing.*, ISBN: 1900222116

Farmani, R., Walters, G.A., and Savic, D.A., (2004). "Trade-off between Total Cost and Reliability for Any town Water Distribution Network". *Journal of Water Resources Planning and Management (ASCE).*, 131 (3) 161-171.

Field, D. B., (1978). Effects of Domestic Storage on Demand Patterns. *WRC Technical Report*, Stevenage Laboratory

Freni, G., La Logioa., Termini, D., and Vitellaro, P., (2004). "A Water Demand Model by Means of the Artificial Neural Network Method". *Proceedings of International conference on Hydro Informatics Singapore- 2004.,* 1473-1480.

Fujiwara, O., and Li, J., (1998). "Reliability Analysis of Water Distribution Networks in Consideration of Equity, Redistribution, and Pressure-Dependent Demand". *Water Resources Research.,* 34 (7) 1843-1850.

Fujiwara, O., and Ganesharaja, T., (1993). "Reliability Assessment of Water Supply Systems with Storage and Distribution Networks". *Water Resources Research.,* 29 (8) 2917-2924.

Fujiwara, O., and Tung, H.D., (1991). "Reliability Improvement for Water Distribution Networks Through Increasing Pipe Size". *Water Resources Research.,* 27 (7) 1395-1402.

Fujiwara, O., and De Silva, A.U., (1990). "Algorithm for Reliability-Based Optimal Design of Water Networks ".*Journal of Environmental Engineering (ASCE).,* 116 (3) 575-587.

Gargano, R., and Pianese, D., (1997). "Reliability as Tool for Hydraulic Network Planning". *Journal of Hydraulic Engineering.,* 126 (5) 354-364.

Germanopoulos, G., (1988). Modelling and Operational Control of Water Supply Networks. Thesis Presented to the University of London, at London, UK in partial fulfillment of the requirement for the degree of Doctor of Philosophy.

Germanopoulos, G., Jowitt, P. W., and Lumbers, J.P., (1986). "Assessing the Reliability of Supply and Level of Service for Water Distribution Systems". *Water Engineering Group.,* 413-428.

Giribone, R., and Valette, B., (2004). "Principles of Failure Probability Assesment (PoF)". *Pressure Vessels and Piping.,* 81 797-806.

Gorantiwar, S.D., and Smout, I., (2005). "Performance assessment of irrigation water management of heterogeneous irrigation schemes : 1. A framework for evaluation", *Irrigation and Drainage Systems.,*19.,2005 pp 1-36.

Goulter, I. C., and Bouchart, F., (1988). "Reliability-Constrained Pipe Network Model". *Journal of Hydraulic Engineering (ASCE).,* 116 (2) 211-229.

Goulter, I.C., and Coals, A.V., (1986). "Quantitative Approaches to Reliability Assessment in Pipe Networks". *Journal of Transportation Engineering (ASCE).,* 112 (3) 104-113.

Goulter, I. C., Davidson, J., and Jacobs, P., (1993). "Predicting water main breakage rate." *Journal of Water Resources Planning and Management, ASCE,* 119(4) 419-436.

Goulter, I. C., and Kazemi, A., (1988). "Spatial and temporal groupings of water main pipe breakage in Winnipeg." *Canadian Journal of Civil Engineering,* 15(1) 91-97.

Guercio, R., and Xu, Z., (1995). "Linearized Optimization Model For Reliability-Based Design of Water System ". *Journal of Hydraulic Engineering.,* 123 (11) 1020-1026.

Gupta, R., and Bhave, P.R., (1993). "Reliability-Based Design of Water-Distribution Systems". *Journal of Environmental Engineering (ASCE).*, 122 (1) 51-54.

Gupta, R., and Bhave, P.R., (1994). "Reliability Analysis of Water-Distribution Systems". *Journal of Environmental Engineering (ASCE).*, 120 (2) 447-460.

Gupta, R., and Bhave, P.R., (1996). "Comparison of Methods for Predicting Deficient-Network Performance". *Journal of Water Resources Planning and Management (ASCE).*, 122 (3) 214-217.

Gustafson, J. M., and Clancy, D. V., (1999). "Modelling the occurrence of breaks in cast iron water mains using methods of survival analysis." *Proceeding of the AWWA Annual Conference*, Chicago.

Haimes, Y.Y., Matalas, N.C., Lambert, J.H.., Jackson, B.A., and Fellows, F.R., (1997). "Reducing Vulnerability of Water Supply Systems to Attack ". *Journal of Infrastructure Systems* ., 4 (4) 164-177.

Han, D., and Cluckie, I.D., (2004). "Support Vector Machines Identification for Runoff Modeling"., *Proceedings of International conference on Hydro Informatics Singapore- 2004.* 1597-1604.

Hartley, J.A., and Powell ,R.S., (1991). "The Development of a Combined Water Demand Prediction System". *Civil Engineering System.*, 8 231-236.

Hecht-Neilson, R., (1989). "Theory of the Back-Propagation Neural Networks," *Proc the International Joint Conference on Neural Networks, Washington, D.C.*, pp. I:593-I:606

Haykin, S., (1994). "Neural Networks: A Comprehensive Foundation". *MacMillan, NY.*

Herz, R. K., (1996). "Ageing processes and rehabilitation needs and strategies for drinking water distribution networks." *Journal of Water Supply Research and Technology-Aqua*, 45(5) 221-231.

Herz, R. K., (1998). "Exploring rehabilitation needs and strategies for water distribution networks." *Journal of Water SRT - Aqua*, 47(6) 275-283.

Hong, H. P., (1998). "Reliability based optimal inspection schedule for corroded pipelines." Proceedings of the annual conference of the Canadian society of civil engineering, Halifax, Nova, Scotia, 743-752.

Hong, H. P., (1997). "Reliability based optimal inspection and maintenance for pipeline under corrosion." Civil Engineering Systems, 14, 313-334.

Huang, W., and Foo, S., (2002). "Neural Network Modeling of Salinity Variation in Apalachicola River". *Water Research.*, 36 356-362.

Huddleston, D. H., Alarcon, V. J., and Chen, W., (2003). "Water Distribution Network Analysis Using Excel". *Journal of Hydraulic Engineering.*, 130 (10) 1033-1035.

IWA (1997) Performance Indicators for Water Supply Services 1st edition, *Tech Report*, eds.,Helena Alegre indicators task force, International Water Association.

IWES (1984) Water Practice manual: *Water Distribution System*, eds., Brandon Thomas, W., Institue of Water Engineers and Scientist. ISBN 0901427136.

Jacobs, P., and Karney, B., (1994). "GIS Development with Application to Cast iron Water Main Breakage Rate". *Proceedings of the 2nd International Conference on Water Pipelines Systems BHR Group Edingburge Scotland.*.

Jankovic-Nisic, B., Maksimovic, C., Butler, D., and Graham, N. J. D., (2004). "Use of Flow Meters for Managing Water Supply Networks". ASCE, *Journal of Water Resources planning and Management.,* 130 (2) 171-179.

Jeppson, R.W., (1980). "Equivalent Hydraulic Pipe for Parallel Pipes". *Journal of the Hydraulics Divisions (ASCE).,* 108 35-45.

Jowitt, P.W., and Xu, C., (1993). "Predicting Pipe Failure Effects in Water Distribution Networks ". ASCE, *Journal of Water Resources planning and Management.,* 119 (1) 18-31.

Jowitt, P.W., and Xu, C., (1992). "Demand Forecasting for Water Distribution Systems". *Civil Engineering System.,* 9 105-121.

Kalungi, R., and Taniyimboh, T.T., (2003). "Redundancy Model for Water Distribution Systems". *Reliability Engineering and System Safety.,* 82 275-286.

Karlsson, P.O., and Haimes, Y.Y., (1988). "Risk Assessment of Extreme Events: Application". *Journal of Water Resources Planning and Management.,* 115 (3) 299-320.

Karaa, F.A., and Marks, D.H., (1989). "Performance of Water Distribution Networks: Integrated Approach ". *Journal of Performance of Constructed Facilities (ASCE).,* 4 (1) 51-67.

Kettler, A.J., and Goulter, I.C., (1985). "An Analysis of Pipe Breakage in Urban Water Distribution Networks". *Department of Civil Engineering, University of Manitoba, Winnipeg, Man.., Canada .,* 12 286-293.

Khanna T., (1989). *Foundations of Neural Networks.* Addison-Wesley Publishing Company, Inc. (ISBN 0-201-50036-1).

Khang, D.B., and Fujiwara, O., (1992). "Optimal Adjacent Pipe Diameters in Water Distribution Networks with Reliability Constraints". *Water Resource Research.,* 28 (6) 1503-1505.

Khomsi, D., Walters, G.A., Thorley, A.R.D., and Ouazar, D., (1996). "Reliability Tester for Water-Distribution Networks". *Journal of Computing in Civil Engineering.,* 10 (1) 10-19.

Kiefner, J. F., and Vieth, P. H., (1989). "Project PR-3-805: a modified criterion for evaluating the remaining strength of corroded pipe." Pipeline Corrosion Supervisory Committee of the Pipeline Research Committee of the American Gas Association.

Kim, J.H., and Mays, L.W., (1993). "Optimal Rehabilitation Model for Water-Distribution Systems". *Journal of Water Resources Planning and Management (ASCE).,* 120 (5) 674-692.

Kim, J.H., and Mays, L.W., (1990). "Rehabilitation and replacement of Water Distribution System Components Considering Uncertainties". *Stochastic Hydrology and Hydraulics.,* 4 277-294.

Kim, J.H., Ko, J.K., Boo, K.M., Woo, H.J., Kim, C.W., Bae, H., and Kim, S.S., (2004). "Software Sensor Using PNN Model and Knowledge- Based for Sequencing Batch Reactor." *Proceedings of International conference on Hydro Informatics Singapore- 2004.* 1361-1368.

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

Kleiner, Y., Adams, B.J., and Rogers, J.S., (1998). "Long-term Planning Methodology for Water Distribution System Rehabilitation". *Water Resources Research.,* 34 (8) 2039-2051.

Kleiner, Y., Adams, B.J., and Rogers, J.S., (1998). "Selection and Scheduling of Rehabilitation Alternatives for Water Distribution Systems". *Water Resources Research.,* 34 (8) 2053-2061.

Kleiner, Y., Adams, B.J., and Rogers, J.S., (1999). "Water Distribution Network Renewal Planning". *Journal of Computing in Civil Engineering.,* 15 (1) 15-26.

Kleiner, Y., and Rajani, B., (1999). "Using Limited Data to Assess Future Needs". *Distribution Systems,* 47-61.

Lam, C. F., and Wolla, M.L., (1972). "Computer Analysis of Water Distribution Systems: Part II-Numerical solutions." *Journal of Hydraulic Division (ASCE),* 93(3) 447-460.

Lansey, K.E., Awumah, K., Zhong, Q., and Goulter, I.C., (1992). "A Supply Based Reliability Measure for Water Distribution Systems". IAHR, *International Symposium on Stochastic Hydraulics.,* 171-178.

Lee, D.S, Park, J.M., and Vanrolleghem, P.A, (1999) "Neural network modeling for on-line estimation of nutrient dynamics in a sequentially-operated batch reactor" *Journal of Biotechnology,* Vol. 75, No. 2, pp 229-239.

Lei, J., (1997). "Statistical approach for describing lifetimes of water mains - Case Trondheim Municipality." *Report No. 22F007.28,* SINTEF Civil and Environmental Engineering, Trondheim, Norway.

Lei, J. H., and Saegrov, S., (1998). "Statistical approach for describing failures and lifetimes of water mains." *Water Science and Technology,* 38(6) 209-217.

Lin, G.F., and Shen, L.H., (2004). "Combining the Radial Basis Functioned Network with the Self Organizing Map for Time Series Forecasting ., *Proceedings of International conference on Hydro Informatics Singapore- 2004* 1425-1432.

Lin, J. L., (1992). *Reinforcement Learning for Robots Using Neural Networks.* Thesis Presented to the Carnegie Mellon University, at Pittsburgh, PA, USA, in partial fulfillment of the requirement for the degree of Doctor of Philosophy.

Loganathan, G. V., Park, S., and Sherali, H. D., (2002). "Threshold break rate for pipeline replacement in water distribution systems." *Journal of Water Resources Planning and Management, ASCE,* 128 (4) 271-279.

Mansoor, M A M., and Vairavamoorthy K. (2005). "Application of Neural Networks for Estimating Nodal Outflows as a Function of Pressure in Distribution Systems". *Proceedings of International Conference on Computing in Civil Engineering.*, Cancun, Mexico 2005.

Maidment, D.R., Miaou, S.P., and Crawford, M.M., (1985). "Transfer Function Models of Daily Urban Water Use". *Water Resources Research.*, 21 (4) 425-432.

Maidment, D.R., and Miaou, S.P., (1986). "Daily Water Use in Nine Cities". *Water Resources Research.*, 22 (6) 845-851.

Maier, H.R., Morgan, N., and Chow, C.W.K., (2004). "Use of Artificial Neural Networks for Predicting Optimal Alum Doses and Treated Water Quality Parameters ". *Environmental Modeling and Software.*, 19 484-494.

Maier, H.R., and Dandy, D.C., (2000). "Neural Networks for Prediction and Forecasting of Water Resources Variables. A Review of Modelling Issues and Applications Environmental Modelling and Soft wave. ". 15 101-124.

Martinez, F., Bou, V., Hernandez, V., Alvarruiz, F., and Alonso, J.N., (2005)"ANN Architectures for Simulating Water Distribution Networks" *Proceedings of International conference on Computing and Control for the Water Industry Exeter UK- 2005.*251-256.

Memon, F., and Butler, D., (2005). "Water Consumption Trends and Demand Forcasting Techniques". Water Demand Management. Butler, D., and Memon, F., eds., IWA publication. pp 1-25.

Marks, H. D., Andreou, S., Jeffrey, L., Park, C., and Zaslavski, A., (1987). "Statistical models for water main failures." US Environmental Protection Agency (Co-operative Agreement CR8 1 0558) M.I.T. Office of Sponsored Projects No. 94211, Boston MA.

Marks, H. D., Andreou, S., Jeffrey, L., Park, C., and Zaslavski, A., (1985). "Predicting urban water distribution maintenance strategies: A case study of New Haven Connecticut." US Environmental Protection Agency (Co-operative Agreement R8 1 0558-01-0).

Maskey, S., Jonoski, A., and Solomatine, D.P., (1999). "Groundwater Remediation Strategy Using Global Optimization Algorithms". *Journal of Water Resources Planning and Management.*, 128 (6) 431-440.

McIntosh, A., and Yniguez, C., (1997). "Second Water Utilities Data Book - Asia and Pacific Region." Asian Development Bank.

McMullen, L. D., (1982). "Advanced concepts in soil evaluation for exterior pipeline corrosion." Proceeding of the AWWA Annual Conference, Miami.

Mays, L. W., (2000). Water distribution systems handbook, McGraw-Hill, New York.

Mays, L.W., (1989). "*New Methodologies for the Reliability-Based analysis and Design of Water Distribution Systems*" Tech.Rep. CRWR 227,Ctr for Res. In Water Resources., University of Texas, Austin Tex.

Oad, R., and Sampath, R. K., (1995). "Performance measures for improving irrigation management." Irrigation and drainage systems, 9, 357-370.

Obradovic, D., and Lonsdale, P., (1998). "Public water suppl: Data, models and operational management." E&FN Spon, New York.

O'Conner, P.D.T., (1995). "Practical Reliability Engineering" John Willey& Sons.

OFWAT, (2007) Levels of Service for the Water Industry in England and Wales (2006-2007) report., 2007.

OFWAT, (2005) Levels of Service for the Water Industry in England and Wales (2004-2005) report., 2005.

O'Garra, R.W., and Stuckey, A.T., (1970). "Hydraulic Considerations in the Design of Pipelines". *Water and Water Engineering.*, 109-115.

Optiwater, (2003). www.optiwater.com/optidesigner

Ormsbee, L., and Kessler, A., (1989). "Optimal Upgrading of Hydraulic-Network Reliability". *Journal of Water Resources Planning and Management (ASCE).*, 116 (6) 784-802.

Ostfeld, A., and Shamir, U., (1993). "Incorporating Reliability in Optimal Design of Water Distribution Networks- Review and New Concepts". *Reliability Engineering and System Safety.*, 42 5-11.

Ostfeld, A., (2004). "Optimal Design and Operation of Multiquality Networks under Unsteady Conditions". *Journal of Water Resources Planning and Management.*, 131(2) 116-124.

Ostfield, A., and Salomons, E., (2003). "Optimal Layout of Early Warning Detection Stations for Water Distribution Systems Security". *Journal of Water Resources Planning and Management .*, 130 (5) 377-385.

Ostfeld, A., (2002). "Water Distribution Systems Connectivity Analysis". *Journal of Water Resources Planning and Management.*, 131 (1) 58-66.

Ostfeld, A., (2001). "Reliability Analysis of Regional Water Distribution Systems". *Urban Water.*, 3 (2001) 253-260.

Ostfeld, A., Kogan, D., and Shamir, U., (2002). "Reliability Simulation of Water Distribution Systems- Single and Multiquality ". *Urban Water.*, 4 53-61.

Osuna, E., Freund, R., and Girosi, F., (1997). "An improved training Algorithm for Support Vector Machines., *Proc.Conference Of the IEEE work shop on Neural Networks for Signal Processing VII, New York*, 276-285.

Pandey, M. D., (1998). "Probabilistic models for condition assessment of oil and gas pipeline." NDT & E International, 31(5) 349-358.

Pelletier, G ., Mailhot, A., and Villeneuve, J.P., (2003). "Modeling Water Pipe Breaks – Three Case Studies ". ASCE, *Journal of Water Resources planning and Management.*, 129 (2) 115 – 123.

Quimpo, R.G., and Shamsi, U.M., (1990). "Reliability-Based Distribution System Maintenance". *Journal of Water Resources Planning and Management (ASCE).*, 117 (3) 321-339.

Rajani, B., and Kleiner, Y., (2001). "Comprehensive review of structural deterioration of water mains: physically based models." *Urban Water*, 3(3) 151-164.

Rajani, B., Makar, J. M., and McDonald, S. E., (2001). "Mechanical properties of grey cast iron water mains." *Journal of Material in Civil Engineering, ASCE*, 1-45.

Rajani, B., Zhan, C., and Kuraoka, S., (1996). "Pipe-soil interaction analysis for joined water mains." *Canadian Geotechnical Journal*, 33(3) 393-404.

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

Randall-Smith, M., Russell, A., and Oliphant, R., (1992). "Guidance manual for the structural condition assessment of the trunk mains." Swindon, UK Water Research Centre.

Rao Vemuri, V., and Robert D. Rogers., "Artificial Neural Networks Forecasting time Series. IEEE Computer Society Press 1994.ISBN 0818651202.

Reddy, S.L., (1990). *Analysis and Design of Pipe Network with Head Dependent Outflows.* Thesis Presented to the Indian Institute of Technology, Madras, at Madras, India in partial fulfillment of the requirement for the degree of Doctor of Philosophy.

Rosegrant, M. W., Cai, X., and Cline, S. A., (2002). "Averting an Impending Crisis." Global Water Outlook to 2025, Food Policy Report,, International Water Management Institute (IWMI),, Colombo, Sri Lanka.

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

Saaty, T L., (1994). "Fundamentals of decision making and priority theory with the AHP."

Pittsburgh: RWS Publications.

Saaty, T L., (1980). "The analytic hierarchy process". New York: McGraw-Hill International.

Schneiter, C.R., Haimes, Y.Y., Li, D., and Lambert, J.H., (1996). "Capacity Reliability of Water Distribution Networks and Optimum Rehabilitation Decision Making". *Water Resources Research.*, 32 (7) 2271-2278.

Seckler, D., D. Molden, and Arker, R., (1998). "Water Scarcity in the Twenty First Century." IWMI Water Brief 1, International Water Management Institute (IWMI), Colombo, Sri Lanka.

Seica, M. V., (2004). "Finite element evaluation of the remaining mechanical strength of deteriorated cast iron pipes." *Journal of Engineering Material Technology*, 126 (1) 95-102.

Seica, M. V., and Packer, J. A., (2004). "Mechanical properties and strength of aged cast iron water pipes." *Journal of Materials in Civil Engineering, ASCE*, 16 (1) 69-77.

Selvakumar, A., Clark, R.M., and Sivaganesan, M., (2000). "Costs for Water Supply Distribution System Rehabilitation ". *Journal of Water Resources Planning and Management.,* 128 (4) 303-306.

Shamir, U., and Howard, C.D.D., (1981). "Water Supply Reliability Theory". *American Water Works Association.,* 379-384.

Shamir, U., and Howard, C.D.D., (1979). "An Analytic Approach to Scheduling Pipe Replacement".*Management and Operations (AWWA).,* 71 (5) 248-258.

Shinstine, D.S., Ahmed, I., and Lansey, K.E., (2001). "Reliability/Availability Analysis of Municipal Water Distribution Networks: Case Studies". *Journal of Water Resources Planning and Management.,* 128 (2) 140-151.

Sinha, S., and Pandey, M.D., (2002). "Probabilistic Neural Network for Reliability Assesment of Oil and Gas Pipelines". *Computer-Aided Civil and Infrastructure Engineering.,* 17 320-329.

Sivapragasan, C., Liong, S.Y., and Pasha, M.F.K., (2001). "Rainfall and Runoff Forecasting with SSA_SVM Approach". *Journal of Hydroinformatics.,* 3 (3) 141-151.

Skipworth, P.J., Saul, A.J., and Machell, J., (1999). "Predicting Water Quality in Distribution Systems Using Artificial Neural Networks "., 1-8.

Smith, L. A., Fields, K. A., Chen, A. S. C., and Trafuri, A. N., (2000). Options for leak and break detection and repair of drinking water systems, Battelle Press, Columbus, Ohio.

Solomatine, D. P., and Price, R. K., (2004). "Innovative approaches to flood forecasting using data driven and hybrid modeling"., *Proceedings of International conference on Hydro Informatics Singapore- 2004.*1639-1646.

Solomatine, D.P., and Dulal, K.N., (2003). "Model Trees as an Alternative to Neural Networks in Rainfall-Runoff Modeling". *Hydrological Sci-Journal-des Sciences Hydrologiques.,* 48 (3) 399-411.

Solomatine, D.P., and Torres, L.A.A., (1996). "Neural Network Modeling of Salinity Variation in Apalachicola River". *Hydroinfomatics'96Muller (ed) 1996 Balkema, Rotterdam.ISBN 9054108525.,* 201-206.

Stephens, D. R., (1994a). "Research seeks more precise corrosion defect assessment: part1." Pipe Line Industry, 7, 45-49.

Stephens, D. R., (1994b). "Research seeks more precise corrosion defect assessment: part 2." Pipe Line Industry, 8 (52-55).

Su, Y.C., Mays, L. W., Duan, N., and Lansey, K.E., (1987). "Reliability Based Optimisation Model for Water Distribution Systems". *Journal of Hydraulic Engineering (ASCE).,* 114 (12) 1539-1556.

Summers, P., (2001). "Finding your way." Journal American Water Works Association, 93 (11) 58-61.

Swamee, P.K., and Sharma, A.K., (1988). "Decomposition of Large Water-Distribution Systems". *Journal of Environmental Engineering (ASCE).*, 116 (2) 269-283.

Swingler K., (1996). *Neural Applying Neural Networks-A Practical Guide.* 1st edition, Harcourt Brace &Company Publishers (ISBN 0-12-679170-8).

Tabesh, M., Tanyimboh, T.T., and Burrows, R., (2004). "Pressure Dependent Stochastic Reliability Analysis of Water Distribution Networks ".*Water science and technology: Water Supply.*, 4 (3) 81-90.

Tabesh, M., Tanyimboh, T.T., and Burrows, R., (2002). "Head-Driven Simulation of Water Supply Networks ".*IJE Transaction.*, 15 (1) 11-22.

Tahar, B., Templemen, A., and Tanyimboh, T.T., (2002). "Pressure-Dependent Modeling of Water Distribution Systems". *Journal of Water Resources Planning and Management (ASCE).*

Tanyimboh, T.T., and Kalungi, P., (2004). "Reply to Comments on 'Redundancy Model for Water Distribution Systems' ".*Reliability Engineering and System Safety.*, 11686 335-337.

Tanyimboh, T.T., Tabesh, M., and Burrows, R., (2001). "Appraisal of Source Head Methods for Calculating Reliability of Water Distribution Networks". *Journal of Water Resources planning and management,* 127 (4) 206-213.

Tanyimboh, T.T., and Sheahan, C., (2000). "A Maximum Entropy Based Approach to the Layout Optimization of Water Distribution Systems ".*Civil.Eng. and Env.Syst.*, 19 (3) 223-253.

Tanyimboh, T.T., and Kalungi, P., (1999). "Reliability-Based Optimal Design of Water Distribution Networks". *Journal of Water Resources Planning and Management.*, 125 (6) 278-280.

Tanyimboh, T.T., Burd, R., Burrows, R., and Tabesh, M., (1999). "Modeling and Reliability Analysis of Water Distribution Systems" *Journal of Water Resources Planning and Management (ASCE).* 39 (4) 249-255.

Tanyimboh, T.T., and Templeman, A.B., (1998). "An Investigation of the Relationship between the Reliability and Entropy of Water Distribution Systems ". 921-932.

Tanyimboh, T.T., and Tabesh, M., (1997). Discussion of "Comparison of Methods for Predicting Deficient Network Performance" *Journal of Water Resources Planning and Management (ASCE).* 123 (6) 369-370.

Tanyimboh, T.T., and Templeman, A.B., (1992). "Optimum Design of Flexible Water Distribution Networks" *Journal of Water Resources Planning and Management (ASCE),* 10 243-258.

Todini, E., (2000). "Looped Water Diastribution Networks Design Using a Resilience Index Based Heuristic Approach ".*Urban Water.*, 115-122.

Thorley, A. R. D., (1991). "Fluid Transients in Pipeline Systems" D & L, George Publisehrs, ISBN 0951783009.

USEPA, (2000). www.epa.gov/nrmrl/wswrd/epanet.html

Vairavamoorthy, K., (1990). *Reliability Assessment of Water Distribution Systems.* Thesis Presented to the University of London, at London, UK in partial fulfillment of the requirement for the degree of Master of Science.

Vairavamoorthy, K., (1994). *Water Distribution Networks: Design and Control of Intermittent Supply.* Thesis Presented to the University of London, at London, UK in partial fulfillment of the requirement for the degree of Doctor of Philosophy.

Vairavamoorthy, K., Elango, K., and Totsuka, N., (2004). "Intermittent Urban Water Supply under Water Starving Situation". *Proc.30th WEDC International Conference, Vientiane, Lao PDR.*

Van Zyl, J.E., Savic, D.A., and Walters, G.A.. "An Explicit Intergration Technique for Dynamic Modeling Of Water Distribution Systems ".

Vemuri, V. R., and Rogers, R. D., (1994). "Artificial neural networks: Forecasting time series" IEEE Computer Society Press, Los Alamitos, CA.

Vojinovic, Z., and Kecman, V., (2004). "Contaminant Transport Modeling with Support Vector Machine Model- An Alternative to Classical Advection- Disposition Equation. *Proceedings of International conference on Hydro Informatics Singapore- 2004* 1589-1596.

Wagner, J.M., Shamir, U., and Marks, D.H., (1988a). "Water Distribution Reliability: Analytical Methods". *Journal of Water Resources Planning and Management (ASCE).,* 114 (3) 253-275.

Wagner, J.M., Shamir, U., and Marks, D.H., (1988b). "Water Distribution Reliability: Simulation Methods". *Journal of Water Resources Planning and Management (ASCE).,* 114 (3) 276-294.

Walski, T.M., and Pelliccia, A., (1982). "Economic Analysis of Water Main Breaks ". *Research and Technology (AWWA).,* 74 (3) 140-147.

Walski, T.M., (1984). "Case Study: Pipe Network Model Calibration Issues". *Journal of Water Resources Planning and Management (ASCE).,* 112 (2) 238-249.

Walski, T.M., (1993). "Practical Aspects of Providing Reliability in Water Distribution Systems". *Reliability Engineering and System Safety.,* 42 13-19.

Walters, G.A., Halhal. D., Savic. D., and Ouazar, D., (1999). "Improved Design of "Anytown" Distribution Network Using Structured Messy Genetic Algorithms". *Urban Water.* 23-38.

Watkins, T. M., and Spangler, M. G., (1958). "Some characteristics of the modulus of passive resistance of soil - a study in similitude." Highway Research Board Proceedings, 37, 576-583.

WHO study group (1987). "Technology for Water Supply and Sanitation in Developing Countries" *Tech Rep Series 743,* World Health Organisation ,Geneva.

Wu, S.J., and Quimpo, R.G., (1992). "Predictive Model and Reliability Analysis for Water Distribution Systems".

Xie, L., (1998). "Pipe Segment Failure Dependency Analysis and System Failure Probability Estimation". *International Journal of Pressure Vessels and Piping.,* 75 483-488.

Xu, C., and Powell, R.S., (1991). "Water Supply System Reliability: Concepts and Measures". *Civil Engineering System.* 8 191-195.

Xu, C., and Goulter, I.C., (1998). "Probabilistic Model for Water Distribution Reliability". *Journal of Water Resources Planning and Management (ASCE).*, 124 (4) 218-228.

Yan, J., (2006). *Modeling Contaminant Intrusion into Urban Water Supply Pipe Networks.* Thesis Presented to the University of Loughborough, at Loughborough, UK in partial fulfillment of the requirement for the degree of Doctor of Philosophy.

Yan J. M., Vairavamoorthy, K., and Gorantiwar, S.D., 2006: "Contaminant transport model for unsaturated soil using fuzzy approach", *Journal of Environmental Engineering (ASCE),* 132 (11) 1489-1497,

Yan, J. M., Vairavamoorthy, K., and Lin, Z. H., (2002a). "Modelling polluted area and variable concentration of contaminant movement through soil." *Proc. 2nd International Postgraduate Research Conference in the Built and Human Environment*, PP 528-537, 11-12 April 2002, University of Salford, UK

Yan, J.M., and Vairavamoorthy, K., (2003b). "Prioritizing Water Mains Rehabilitation Under Uncertainty" *Proc.Advances In Water Supply Management International conference.,* Imperial College,London,UK,15-18 September 2003:237-246

Yang, S.L., Hsu, N.S., Louie, P.W.F., and Yeh, W.W.G., (1995). "Water Distribution Network Reliability: Connectivity Analysis". *Journal of Infrastructure Systems (ASCE).*, 2 (2) 54-64.

Yang, S.L, Hsu, N.S., Louie, P.W.F., and Yeh, W.W.G., (1995). "Water Distribution Network Reliability: Stochastic Simulation". *Journal of Infrastructure Systems.*, 2 (2) 65-72.

Yuebin, W., Jinliang, G., and Hongbin, Z., "An Approach to Performance Assessment for Water Distribution Systems".

Zessler, U., and Shamir, U., (1987). "Optimal Operation of Water Distribution Systems". *Journal of Water Resources Planning and Management.*, 115 (6) 735-751.

Zyl, J.V., Savic, D.A., and Walters, G.A., "Some Accuracy Issues in Extended Period Modeling of Water Distribution Systems ".

APPENDIX 1

The 30 node network

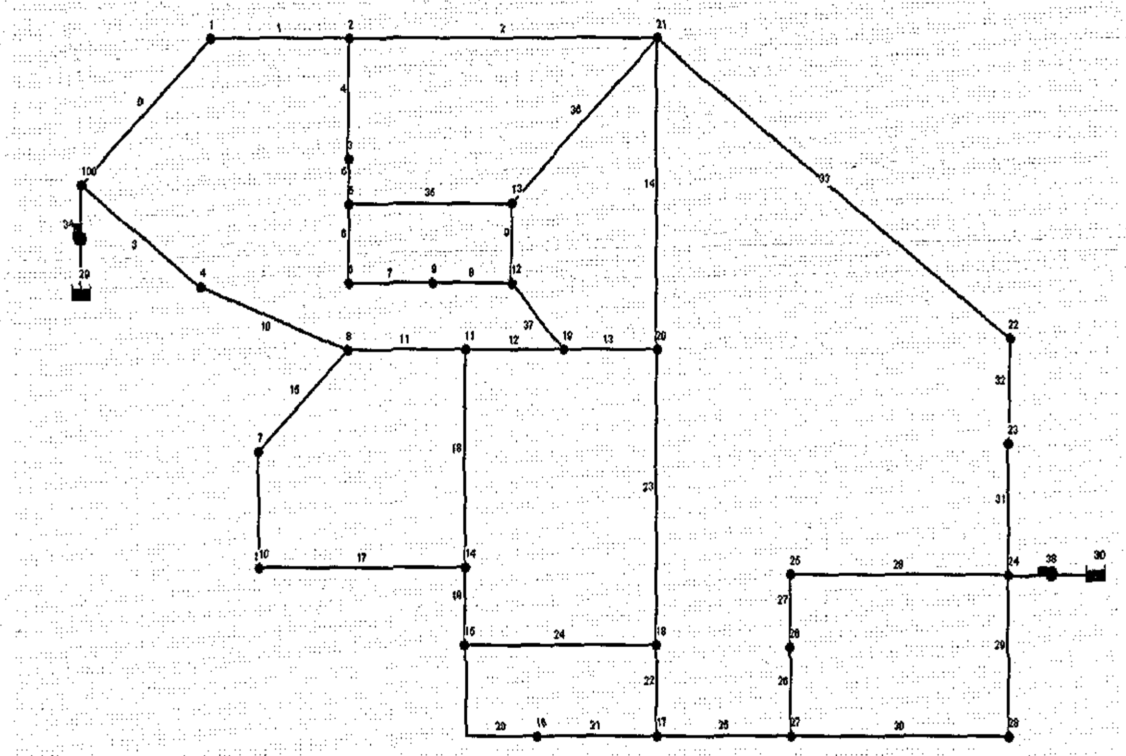


Figure A1.1: Schematic of 30 node network

Table A1.1: Pipe data for 30 node network

Pipe ID	Diameter (mm)	Length (km)	Failure Probability	MTBF(Years)
1	300	0.3	0.24	3.70
2	300	0.3	0.22	4.03
3	300	0.3	0.38	2.08
4	300	0.3	0.44	1.72
5	300	0.3	0.19	4.68
6	250	0.25	0.09	10.48
7	250	0.25	0.08	11.70
8	250	0.25	0.12	8.06
9	150	0.15	0.11	8.33
10	150	0.15	0.23	3.93
11	250	0.25	0.15	6.35
12	300	0.3	0.18	5.10
13	200	0.2	0.21	4.31
14	200	0.2	0.21	4.29
15	200	0.2	0.11	8.62
16	300	0.3	0.32	2.57
17	150	0.15	0.17	5.24
18	300	0.3	0.08	11.79
19	150	0.15	0.30	2.80
20	250	0.25	0.10	9.58
21	300	0.3	0.09	10.78
22	300	0.3	0.08	11.79
23	300	0.3	0.23	3.81
24	300	0.3	0.31	2.74
25	300	0.3	0.35	2.37
26	150	0.15	0.11	8.33
27	300	0.3	0.35	2.37
28	150	0.15	0.29	2.98
29	150	0.15	0.23	3.93
30	200	0.2	0.33	2.53
31	300	0.3	0.37	2.15
32	300	0.3	0.09	10.78
33	300	0.3	0.08	11.79
34	300	0.3	0.07	14.71
35	150	0.15	0.32	2.60
36	300	0.3	0.11	8.33

Table A1.2: Node data for 30 node network

Node No	Elevation (m)	Demand (l/s)
1	35.28	1.08
2	DN	DN
3	31.5	0.46
4	31.36	0.48
5	34.21	2.26
6	31.23	0.66
7	31.18	0.38
8	26.89	1.04
9	30.4	0.64
10	30.74	0.66
11	26.88	1.32
12	26.4	1.22
13	29.88	0.64
14	29.83	1.16
15	26.11	1.64
16	25.32	3.34
17	25.18	1.44
18	24.74	1.28
19	22.96	0.58
20	25.49	0.86
21	24.74	1.5
22	26.51	1.58
23	DN	DN
24	25.65	3.19
25	25.55	2.18
26	25.44	1.19
27	25.34	1.56
28	25.29	0.98
29	25.22	4.21
30	25.25	1.48

Pump Details.

Both the pumps supplying the network has a characteristics curve which has the form of ;

$$H = 100 - 0.04Q^2 \qquad \text{A1.1}$$

Where
H – Head (m)

Q – Flow (l/s)

Table A1.3: Secondary network details of the 30 node network.

Node No	Secondary network length	No of Branches	Average demand	No of consumers
1	530	4	1.08	467
2	DN	DN	DN	DN
3	480	3	0.46	199
4	495	3	0.48	208
5	950	5	2.26	977
6	500	3	0.66	286
7	450	3	0.38	165
8	545	4	1.04	450
9	500	3	0.64	277
10	505	3	0.66	286
11	600	4	1.32	571
12	550	4	1.22	528
13	510	3	0.64	277
14	535	4	1.16	502
15	800	4	1.64	709
16	1240	6	3.34	1443
17	570	4	1.44	623
18	560	4	1.28	553
19	498	3	0.58	251
20	520	3	0.86	372
21	585	4	1.5	648
22	595	4	1.58	683
23	DN	DN	DN	DN
24	1200	6	3.19	1379
25	900	5	2.18	942
26	555	4	1.19	515
27	590	4	1.56	674
28	540	4	0.98	424
29	1430	7	4.21	1819
30	580	4	1.48	640

Key:
DN- Dummy node

A1.1 Weight Factor for Nodes

The weights for understanding the consumers' failure experience were obtained by interviewing the respondents and analysing their responses based on their opinion. For this purpose a questionnaire was prepared. 15 consumers types grouped into 4 major categories were identified for this region. The consumer types may vary from node to node. For example at Node-1, there may be 4 types of consumers (household with storage, household without storage, care homes and schools) and at another node there may be 3 types of consumers (business, offices, restaurants). The general form of questionnaire considering that all types of consumer at particular node is given below.

As stated below in the guidelines, the respondents were provided with the information on the characteristics of each consumer type and the percentage of population of each consumer type for all the nodes. The respondents were asked to provide the information on "importance" for each node separately as the % of population of each consumer type varies according to nodes and hence the "importance" of particular consumer type varies from node to node.

However the respondents were asked to provide the information on "consequences" for each consumer type separately for the whole region (thus irrespective of the % of population of each consumer type at different nodes).

Typically interviews should be conducted with all the stakeholders involved in the water industry, however, in this thesis only one group of the stakeholders have been considered. Here the purpose is only to demonstrate the applicability of the weights. Therefore initially the methodology employed to determine the weights from one group of stakeholders has been demonstrated. At the end the method to determine weights from different stakeholders based on an Analytic Hierarchy Process (AHP) is shown.

Example questionnaire for assessing importance and consequences of consumers to failure events

A1.1.1 Guidelines:

The details of each type of consumers are provided below.

Household

With additional storage-OHT: Water is needed for domestic purposes. These types of consumers have overhead water tanks. The capacity of the tanks varies from 110 to 410 litres and usually is sufficient to provide buffer stock of water for one whole day.

Without storage: Water is needed for domestic purposes. These types of consumers do not have any water storage and hence are sensitive to failure events. However they have the capability to import water from other sources.

Care homes: Water is needed for domestic purposes but for the people having special needs. The small amount of storage is available. Capability to import water from other sources usually depends on the social worker.

Medical Facilities

Hospitals: The patients are admitted here and they are resident in hospital. Though storage of water is available, the need of water during the failure event might be multi folds than the available storage. The unavailability of water may stop functioning of the medical equipments and cause casualty.

Medical Centres: The general medical practices (or surgery) where people go to see a general practitioner. Water storage is available. The unavailability of water may hinder the day to day functions.

Clinics: The people suffering from different diseases are checked. Usually the water storage is not available. The need of water during failure events depend on the type of diagnosis activities taking place. Some of these activities can be postponed.

Hospice: Where people with terminal illnesses are looked after. Usually water storage is available. Unavailability of water may cause sever disruptions and the consumers are very vulnerable in terms of water need.

Industries

Bulk water use (e.g. Breweries): Water is required in huge amount and the storage for this huge amount is not available. It is quite possible that the operating units will have to be stopped from functioning due to shortage of water. The import of water is not possible.

Business: The storage is not available; the probability that water will be needed during the failure events is less. The activities can be postponed for later date.

Catering: Some storage is available but usually may not be sufficient to cater the needs during the failure event. The activities during failure can be postponed for some time. The import of water is not possible.

Restaurants: Some storage is available and usually sufficient to cater the needs during the failure event. However in case of shortages, the activities during failure cannot be postponed to later time. The import of water is not possible.

Sports and Recreation: The storages required to fulfil the needs during the failure events are not available; import of water is not possible. However the activities can be postponed with some compensation.

Car wash: The storages required to fulfil the needs during the failure events are not available; import of water is not possible. However the activities can be postponed with some loss.

Public Buildings

Schools: Some storage is available; however not usually sufficient to satisfy the huge demand of water. Several school activities will be affected due to shortage of water and is difficult to accommodate many of these activities at later time.

Offices: Storage may not be available, but the need of water is usually small and many activities during the event of failure can be rescheduled with inconvenience to people.

The following is the example of assessing the importance and consequences of different consumers to failure events.

Household (With additional storage – OHT)

What is the importance of water to household (with additional storage – OHT)?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to household (with additional storage – OHT) in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Household (without storage)

What is the importance of water to household (without storage)?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to household (without storage) in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Care homes

What is the importance of water to care homes?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to care homes in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Medical facilities- Hospitals

What is the importance of water to hospitals?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to hospitals in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Medical facilities- Medical Centres

What is the importance of water to medical centres?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to medical centres in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Medical facilities- Clinics

What is the importance of water to clinics?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to clinics in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Medical facilities- Hospice

What is the importance of water to hospice?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to hospice in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Industries- Bulk water use

What is the importance of water to bulk water use industries?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to bulk water use industries in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Industries- Business

What is the importance of water to business?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to business in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Industries- Catering

What is the importance of water to catering business?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to catering business in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Industries- Restaurants

What is the importance of water to restaurants?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to restaurants in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Industries- Sports and Recreation

What is the importance of water to sports and recreation utilities?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to sports and recreation utilities in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Industries- Car wash

What is the importance of water to car wash centres?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to car wash centres in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Public buildings-Schools

What is the importance of water to schools?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to schools in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

Public buildings-Offices

What is the importance of water to offices?		
❑ Very low ❑ Low	❑ Average	❑ High ❑ Very High

How do you consider the consequences to offices in the event of failure of water supply?		
❑ Not very severe ❑ Not severe	❑ Average	❑ Severe ❑ Very severe

The questionnaire was sent to the selected individuals (4 from water companies an 1 academic). The experts from Water Company were contacted by telephone and the academic at the Loughborough University was interviewed directly.

Their responses to the question in the questionnaire were in qualitative form. They were converted to quantitative form and average numeric values were derived to evaluate the weights at the nodes.

Table A2 (a) and (b) below shows the typical responses obtained from a respondent. Table A2 (c) indicates the average importance and consequences obtained for node 1 at the water distribution network.

Table A1.2 (a): The consequences to water failure of different consumer types obtained from a typical respondent.

Consumer Type	Consequence
Household	
With additional storage (OHT)	Severe
Without storage	Severe
Care homes	Very Severe
Medical Facilities	
Hospitals	Very severe
Medical Centres	Severe
Clinics	Severe
Hospice	Very severe
Industries	
Bulk water use (e.g. Breweries)	Severe
Business	Not severe
Catering	Severe
Restaurants	Severe
Sports and Recreation	Not Severe
Car wash	Not Severe
Public buildings	
Schools	Severe
Offices	Not Severe

Table A1.2 (b): The importance and consequences (numerical equivalence) to water failure of different consumer types obtained from a typical respondent.

Consumer Type	Importance
Household	
With additional storage (OHT)	0.7
Without storage	0.7
Care homes	0.9
Medical Facilities	
Hospitals	0.9
Medical Centres	0.7
Clinics	0.7
Hospice	0.9
Industries	
Bulk water use (e.g. Breweries)	0.7
Business	0.3
Catering	0.7
Restaurants	0.7
Sports and Recreation	0.3
Car wash	0.3
Public buildings	
Schools	0.7
Offices	0.3

The equivalent numerical values of the responses were obtained using Table 2.2 given in Chapter 2.

Table A1.2 (c): The importance to water failure of different consumer types obtained from a typical respondent for Node-1

Consumer Type	**Importance**	**Consequence**
Industries		
Business	0.67	0.60
Restaurants	0.78	0.77
Sports and Recreation	0.80	0.85
Public buildings		
Offices	0.68	0.74

The average numerical values of importance and consequences were obtained for each category of people. A typical example of average numerical values of importance and consequences is shown in Table A3 for Node 1.

Table A1.3: A typical example for average numerical values of importance and consequences for Noide-1

Consumer Type	Importance	Consequence
Industries		
Business	0.42	0.58
Restaurants	0.78	0.70
Sports and Recreation	0.34	0.90
Public buildings		
Offices	0.34	0.62

The weighted factor for Node is computed by equation (A.3).

$$W_i = \frac{1}{m}\sum_{j=1}^{m} I_j C_j \qquad \text{A.1.2}$$

Where I_j is the importance of the consumer group j, C_j is the consequence of the consumer group j, m is the number of consumer groups and i is the node number.

The weighted average factor for Node-1 obtained using equation (A1.2) = **0.55**

A1.2 Weights obtained using the information from more than one group of stake holders

Typically weights are derived after interviewing different groups of stakeholders such as; consumers, councils, water utilities, water companies. In such situations, the qualitative information obtained from the interviews has to be integrated. This done by using Analytical Hierarchy Process (AHP) which is described below.

The weights of each category of people were obtained from the independent academician working in the field of water industries by interviewing the academician and analysing the response by using Analytical Hierarchy Process (AHP) (Saaty, 1980 and Saaty, 1994). The questionnaire used for obtaining the response of academician for knowing the weights to each group of category is given below. The calculation of weights is presented in Table A4.

Example Questionnaire for AHP

A1.2.1 Guidelines

The questionnaire consists of two columns for each comparison. The respondents are required to tick the choice of preference in the **column 1** and tick the degree of preference in the **column 2** of each comparison.

For example, to compare the two factors of *water user* and *water industry*, if respondent feels water user is more important to know the importance and consequences of failure of water supply to different types of consumers compared to water industry, respondent should tick 'water user in the column-1 of the table and then go to column-2. If respondent thinks that 'water user' is 'strongly contributory' over the 'water industry', then 'strongly preferred' should be ticked in the **column-2** of the table. In this way the respondent is required to complete all the pair-wise comparisons.

1. **Water user- Water industry**

Column-1	Column-2	
❑ Water user ❑ Water industry	❑ Equally preferred ❑ Moderately preferred ❑ Strongly preferred	❑ Very strongly preferred ❑ Extremely preferred
Reasons for preference if any		

2. **Water user-Council**

Column-1	Column-2	
❑ Water user ❑ Council	❑ Equally preferred ❑ Moderately preferred ❑ Strongly preferred	❑ Very strongly preferred ❑ Extremely preferred
Reasons for preference if any		

3. **Water industry-Council**

Column-1	Column-2	
❑ Water industry ❑ Council	❑ Equally preferred ❑ Moderately preferred ❑ Strongly preferred	❑ Very strongly preferred ❑ Extremely preferred
Reasons for preference if any		

Table A1.4: The weights to each category of respondent as obtained by AHP from the independent academician.

	Water User	Water industry	Council	Geometric Mean	Priority Vector (weights)	Eigen Value
Water user	1	3	4	2.29	0.62	0.99
Water industry	0.333	1	2	0.87	0.24	1.07
Council	0.25	0.500	1	0.50	0.14	0.96
Add Columns	1.583	4.500	7	3.66	1.00	3.02
					Consistency Index	0.009
					Consistency Ratio	0.016

Pairwise comparison is consistent

The weighted average of average numerical values of importance and consequences are obtained by using the equations (A1.3) and (A1.4).

$$I_j = \sum_{k=1}^{n} w_k i_{jk} \qquad \text{A1.3)}$$

where

I_j = Weighted average of importance of j^{th} consumer

n	=	Total number of categories of respondent
w_k	=	Weight to k^{th} category of respondent
i_{jk}	=	Average numerical value of importance obtained from k^{th} category of respondent for j^{th} consumer

$$C_j = \sum_{k=1}^{n} w_k c_{jk} \qquad \text{(A1.4)}$$

where

C_j	=	Weighted average of consequence to j^{th} consumer
c_{jk}	=	Average numerical value of consequence obtained from k^{th} category of respondent for j^{th} consumer

A typical example of average numerical values of importance and consequence for Node-1 noted by all the three categories of respondents are presented in Table A1.5.

Table A1.5: A typical example of average numerical values of importance and consequence for Node-1 noted by all the three categories of respondents.

Consumer Type	Category of respondent					
	Water users		Water industries		Council	
	Importance	Conseq.	Importance	Conseq.	Importance	Conseq.
Households						
With additional storage (OHT)	0.74	0.62	0.54	0.54	0.58	0.62
Without storage	0.82	0.82	0.66	0.62	0.78	0.82
Care homes	0.82	0.86	0.78	0.78	0.78	0.90
Public buildings						
Schools	0.74	0.74	0.58	0.66	0.62	0.86

The weighted average of importance and consequence for Node-1 is computed with the help of average numerical values of importance and consequence, weights to each category of respondent and equations (A1.3) and (A1.4) and are presented in Table A1.5 as an example.

APPENDIX 2

A2.1 Description of Voronoi Polygons

This section reports on the application of Voronoi polygon as used in this research for creating secondary networks. A Voronoi diagram (a group of Voronoi polygon) is a geometric structure that represents proximity information about a set of points or objects, it is a fundamental data structure appearing in many variants in the Computational Geometry literature (Gold *et. al.,* 1995). Voronoi diagrams represent the partitioning of space into cells such that all locations within any one cell are closer to the generating objects than to any other and thus Voronoi edges are curves of equi-distance between pairs of objects (Gold and Anton Castro 1995).

Voronoi polygons had wide application in over twenty fields among which are: Geography, Geometric modeling, Forestry, linguistics, Marine navigation, Mathematics, Meteorology and Robotics (Kenneth *et. al.,* 1999; Edwards *et. al.,* 19996; Gold and Edwards, 1992; Mioc *et. al.,* 1998; Gold *et al.,* 1998; Drysdale, 1993; Gold and Zhou, 1990). As reviewed by Okabe, Boots *et al.,* 1992), the concept of Voronoi polygons first appeared in the early 1644. Then Voronoi-like diagrams was used to show the disposition of matter in the solar system and its environs. The first man who studied the Voronoi diagram as a concept was a German mathematician G.L. Dirichlet. He studied the two and three-dimensional case and that is why this concept is also known as Dirichlet tessellation. However it is much better known as a Voronoi diagram because another German Mathematician M.G. Voronoi in 1908 studied the concept and defined it for a more general n-dimensional case. Very soon after it was defined by Voronoi it was developed independently in other areas like meteorology and crystallography. Thiessen developed it in meteorology in 1911 as an aid to computing more accurate estimates of regional rainfall averages. In the field of Crystallography German researchers dominated and Niggli in 1927 introduced the term Wirkungsbereich (area of influence) as a reference to a Voronoi diagram. During the years this concept kept being rediscovered over and over again in different fields of science and today it is extensively used in about 15 different fields of sciences.

In this research, the application of Voronoi polygon draws its analogy from current usage in meteorology where regional rainfall averages are estimated based on data at discrete rain gauges. Here, polygon are created over a given water supply network area in order to partition the larger network to smaller and manageable networks (secondary network). Figure A4.3 shows the algorithm for network partitioning using Voronoi polygons.

A point to note when drawing the polygons is that the bisecting lines (B_L) and the connection lines (L_{jk}) are perpendicular to each other. When this rule is used for every point in the area, the area will completely covered by adjacent polygons.

To illustrate this process, a water demand area is shown in Figure A4.1 for which secondary network partition is to be carried out. Figure A4.2 shows an Illustration of network partition using Voronoi polygons. The stars in each partition (secondary networks on Figure A4.2) are created primary nodes from which each secondary network is fed. Hence all secondary nodes within each polygon are assumed to have their demand load concentrated at a created primary node within the polygon.

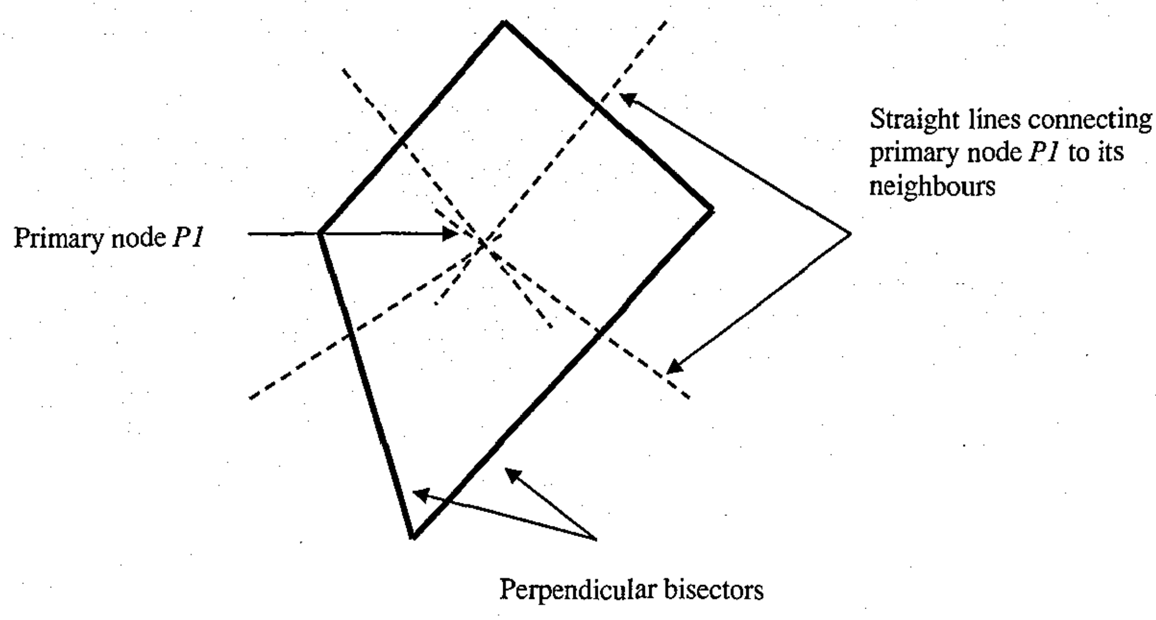


Figure A2.1: Construction of Voronoi Polygon

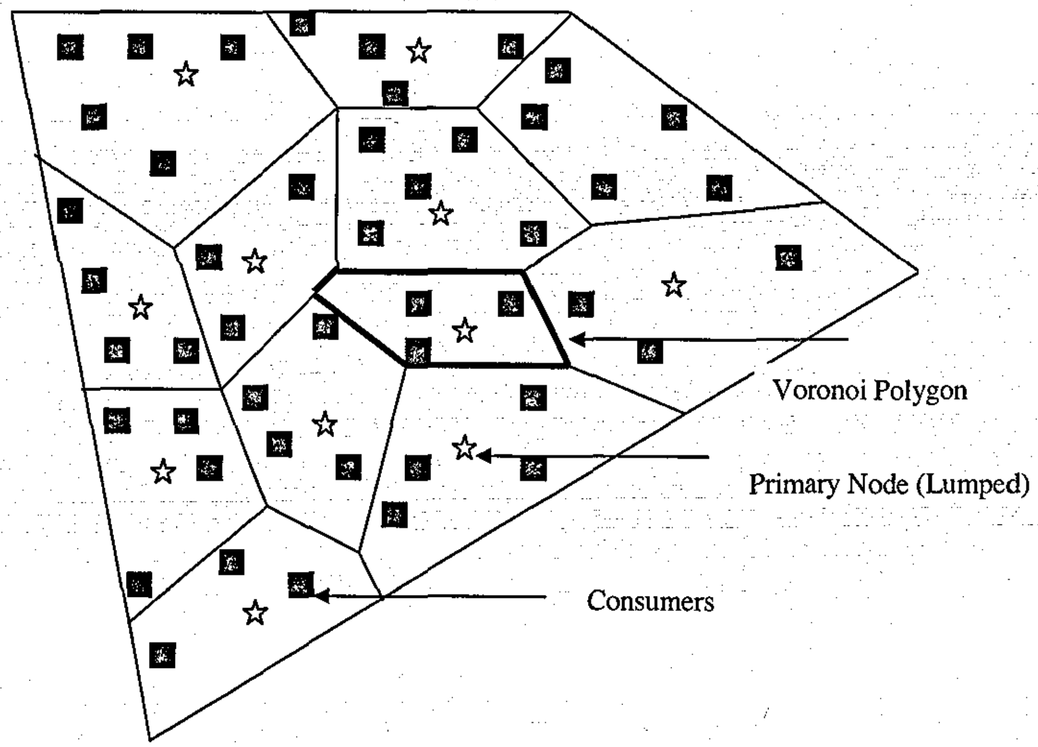


Figure A2.2: Partitioned network

Given: Coordinates of supply area
Given: Coorinates of primary nodes (X_j, Y_j)
Start
{ $j = 1$
{*(Connect each primary node to nearest neighbour)*
Find the nearest neighbours to the primary node (X_j, Y_j)
Draw straight line (L_{jk}) to connect the lumped node to its neighbours
(**For** $k = 1$ to No. of neighbours)
} **While** $(X_j, Y_j = x_n, y_n)$
{*(Bisect all lines connecting nodes)*
Get $L_k (k = 1...N)$
$k = 1$
Draw perpendicular bisectors B_L to L_k
(**For** $L = 1$ to No. of bisectors)
} **While** $(k \leq N)$
Draw the Voronoi polygon (defined by B_L around each lumped secondary node (X_j, Y_j))
}

Figure A2.3: Algorithm for network partitioning using Voronoi polygons

Appendix 3

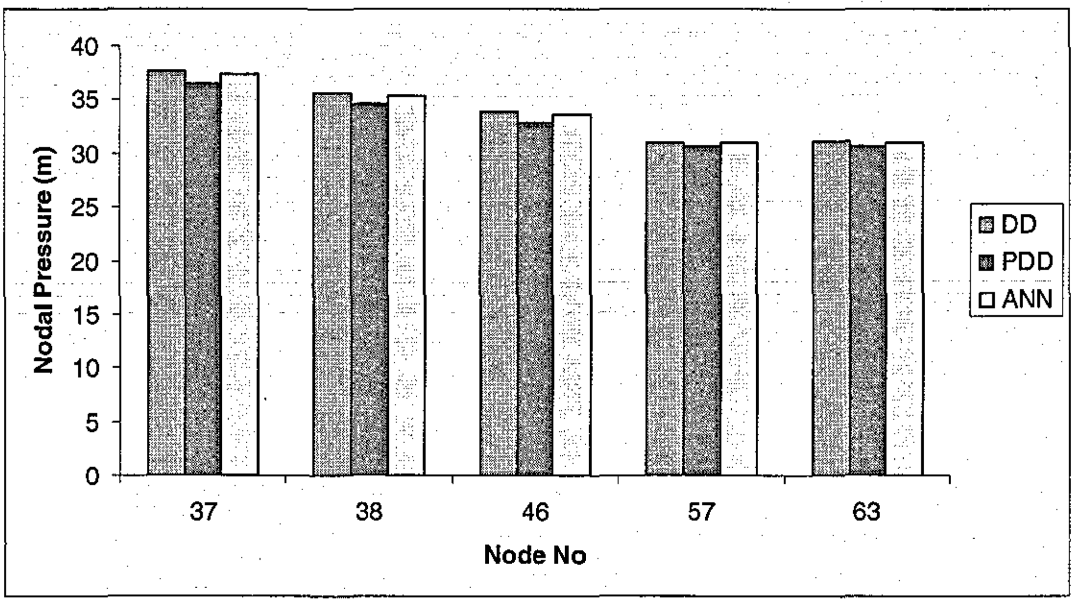


Figure A 3.1 a: Pressures at nodes during normal operations at 9 am

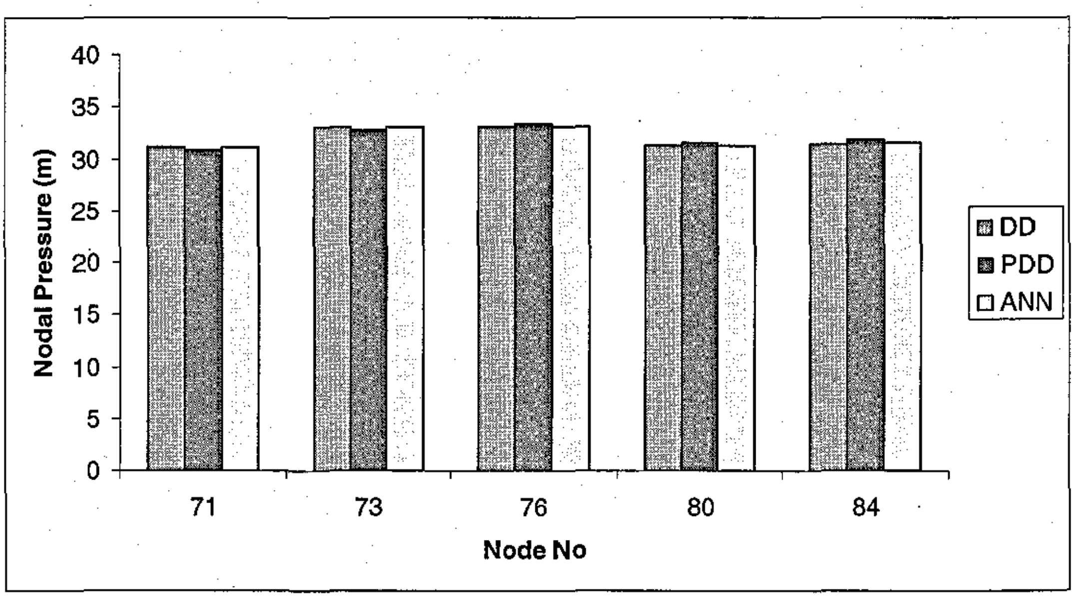


Figure A 3.1 b: Pressures at nodes during normal operations at 9 am

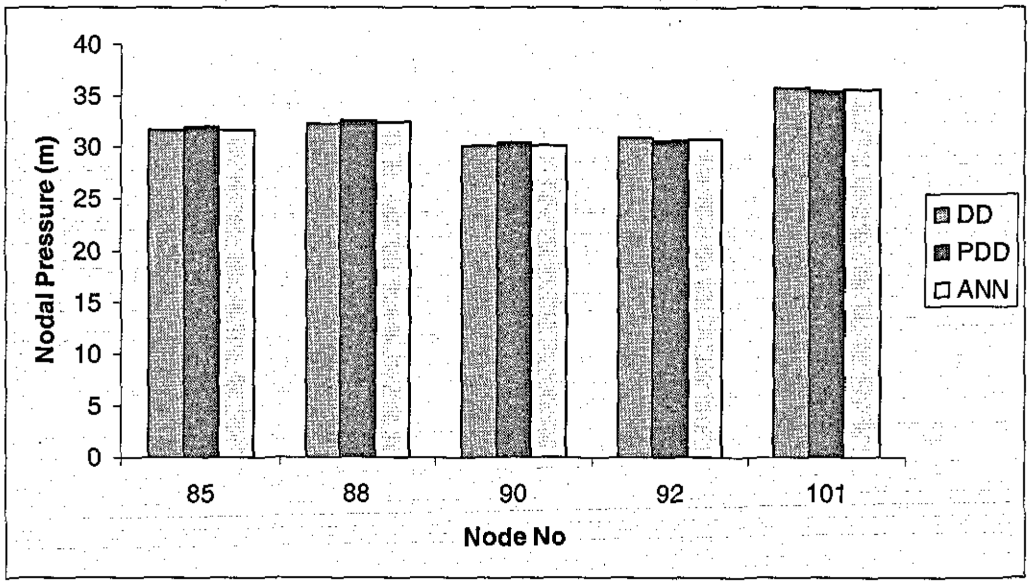


Figure A 3.1 c: Pressures at nodes during normal operations at 9 am

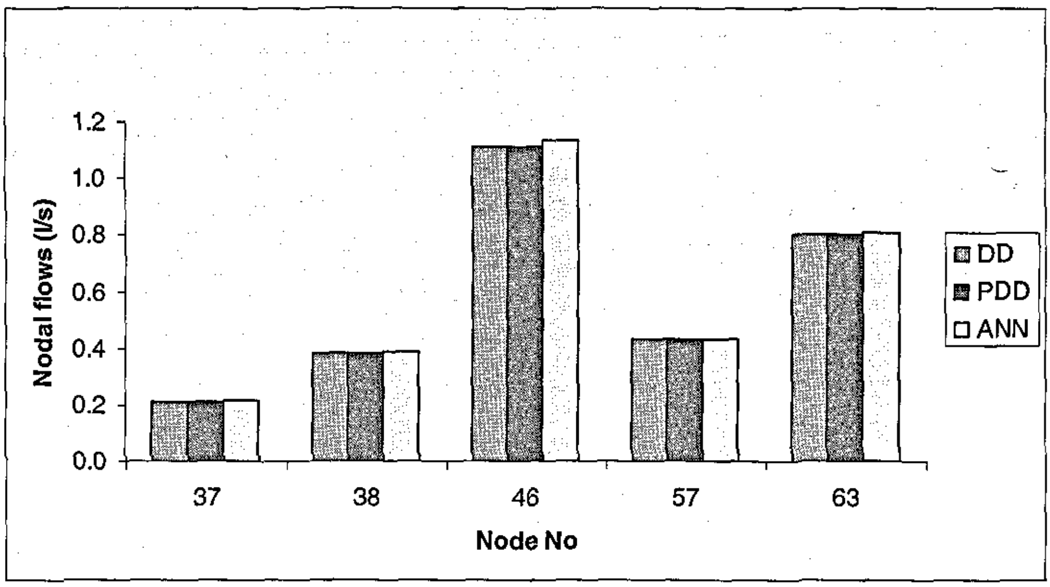


Figure A 3.2 a: Flows at nodes during normal operations at 9 am

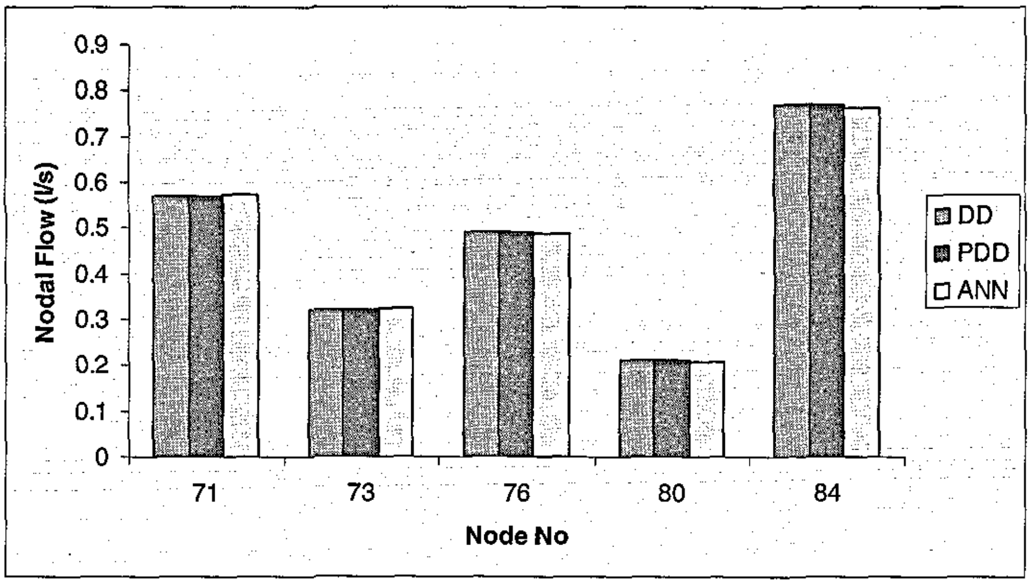


Figure A 3.2 b: Flows at nodes during normal operations at 9 am

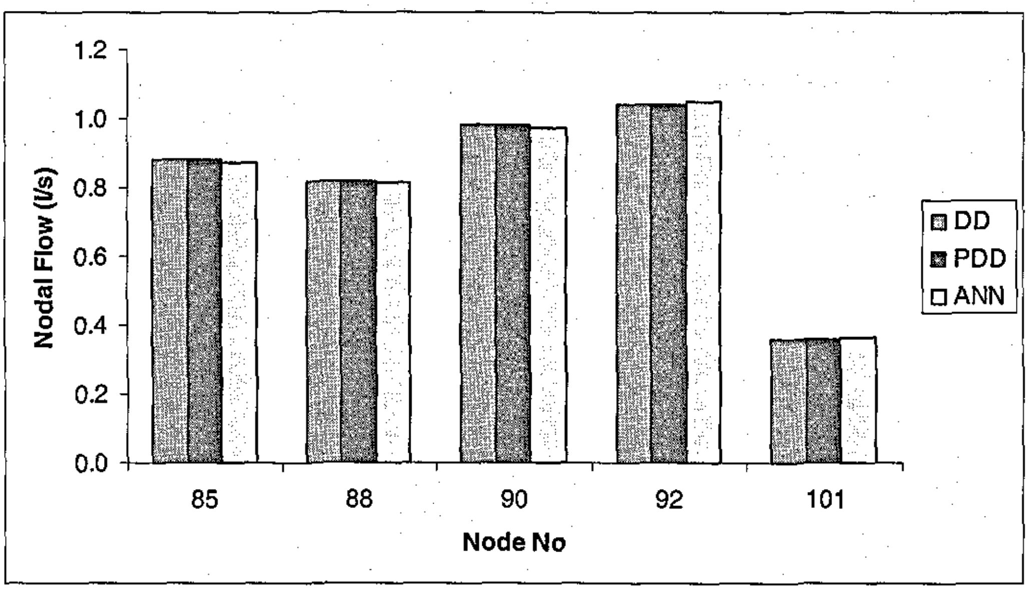


Figure A 3.2 c: Flows at nodes during normal operations at 9 am

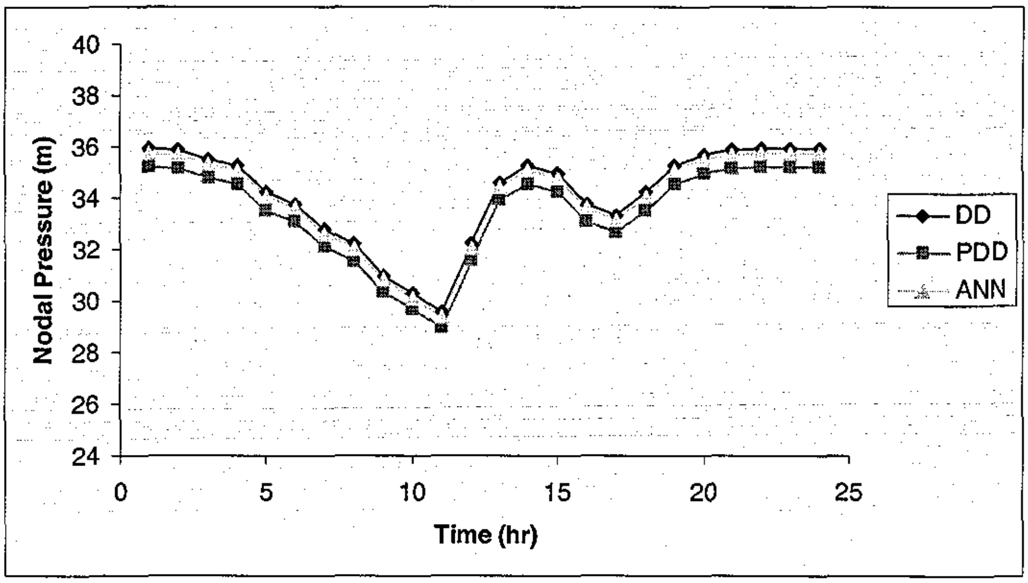


Figure A 3.3 a: Pressure variation at node 17 during normal operation

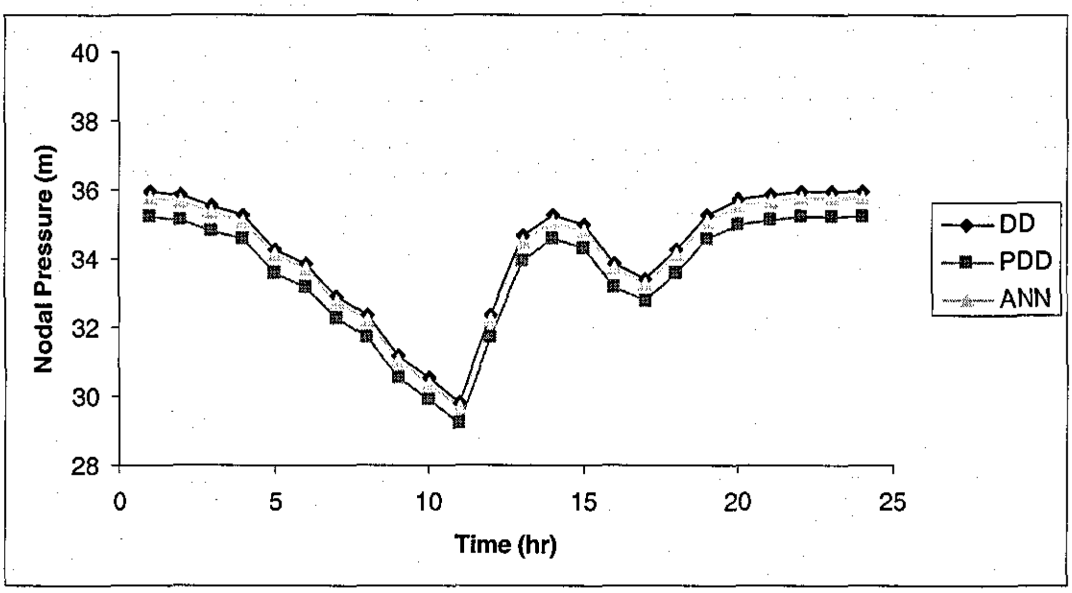


Figure A 3.3 b: Pressure variation at node 71 during normal operation

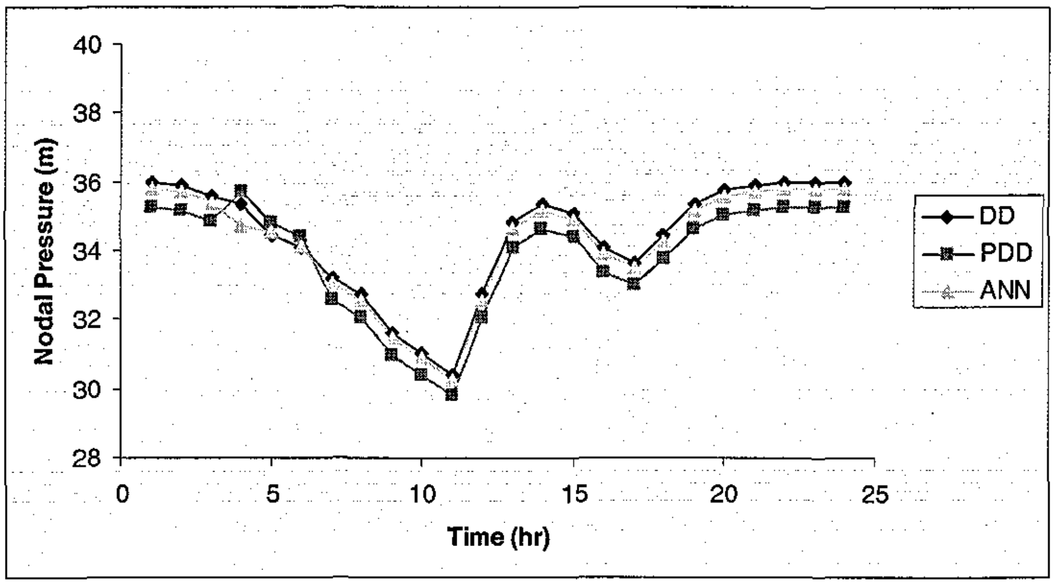


Figure A 3.3 c: Pressure variation at node 85 during normal operation

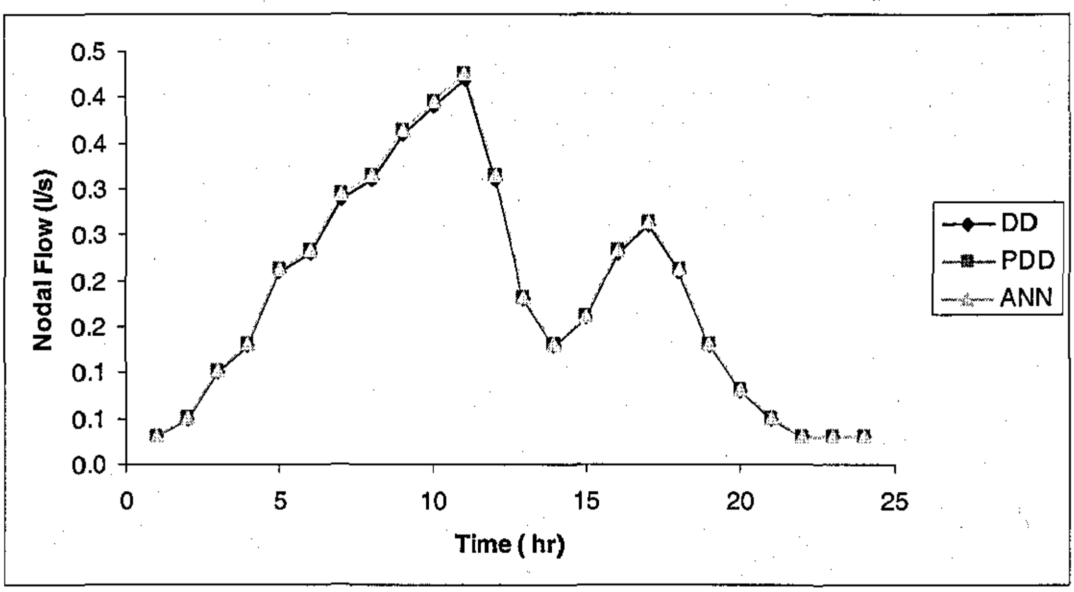


Figure A 3.4 a: Flow variation at node 17 during normal operation

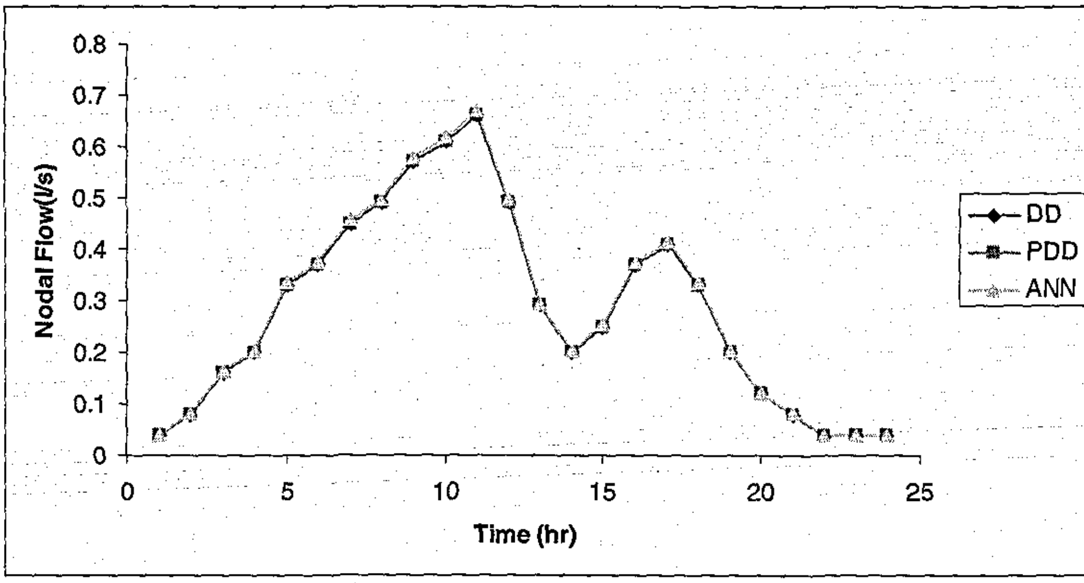


Figure A 3.4 b: Flow variation at node 71 during normal operation

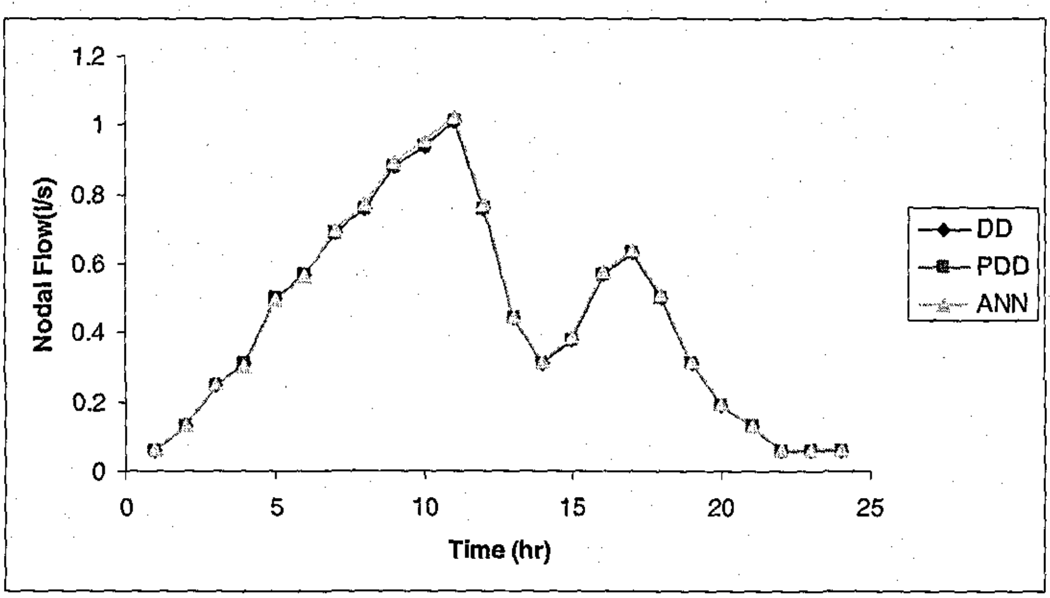


Figure A 3.4 c: Flow variation at node 71 during normal operation

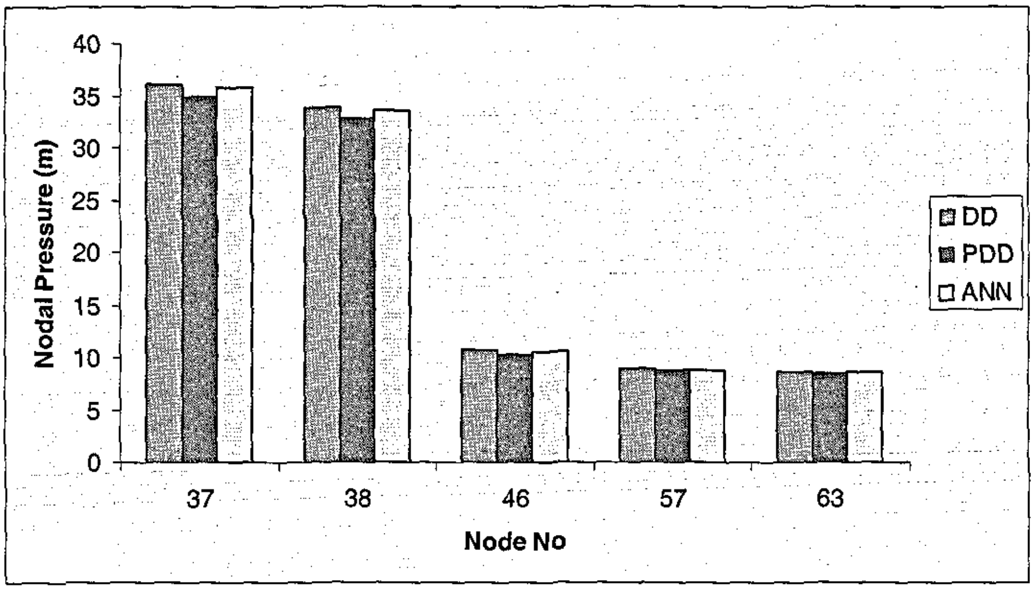


Figure A 3.5 a: Pressures at nodes during failure of pipe 46 at 9 am

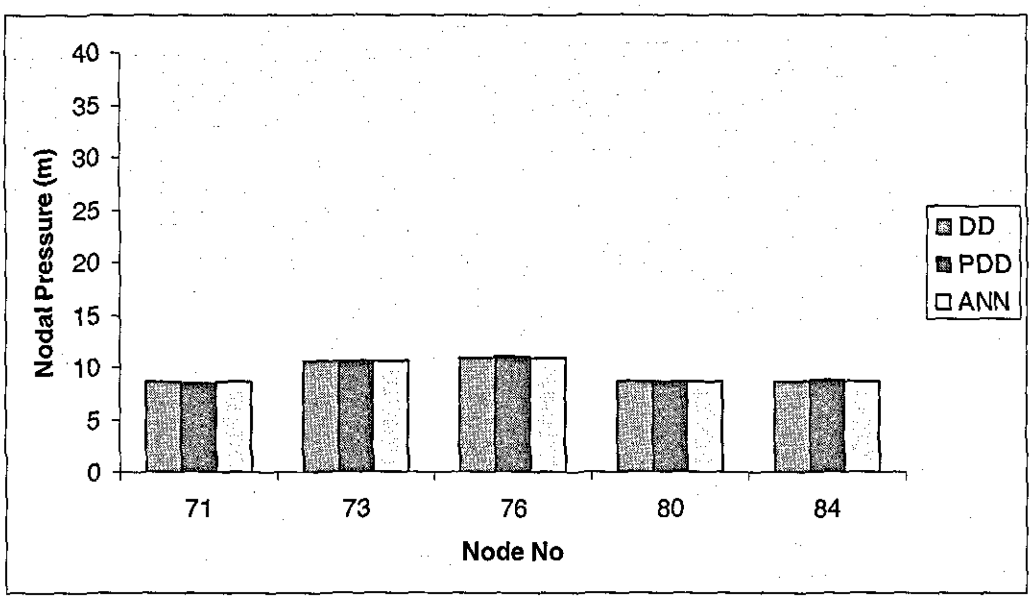


Figure A 3.5 b: Pressures at nodes during failure of pipe 46 at 9 am

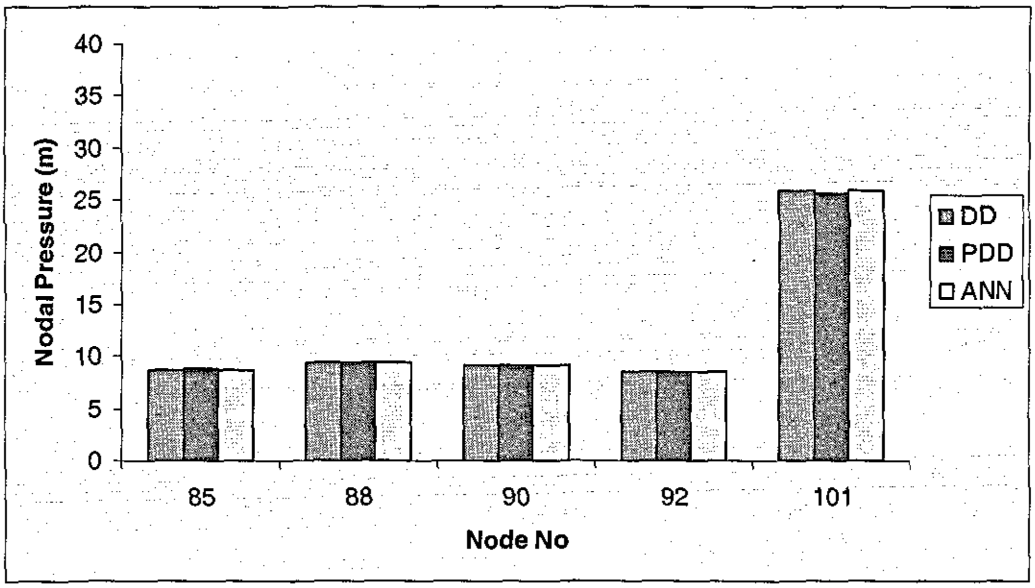


Figure A 3.5 c: Pressures at nodes during failure of pipe 46 at 9 am

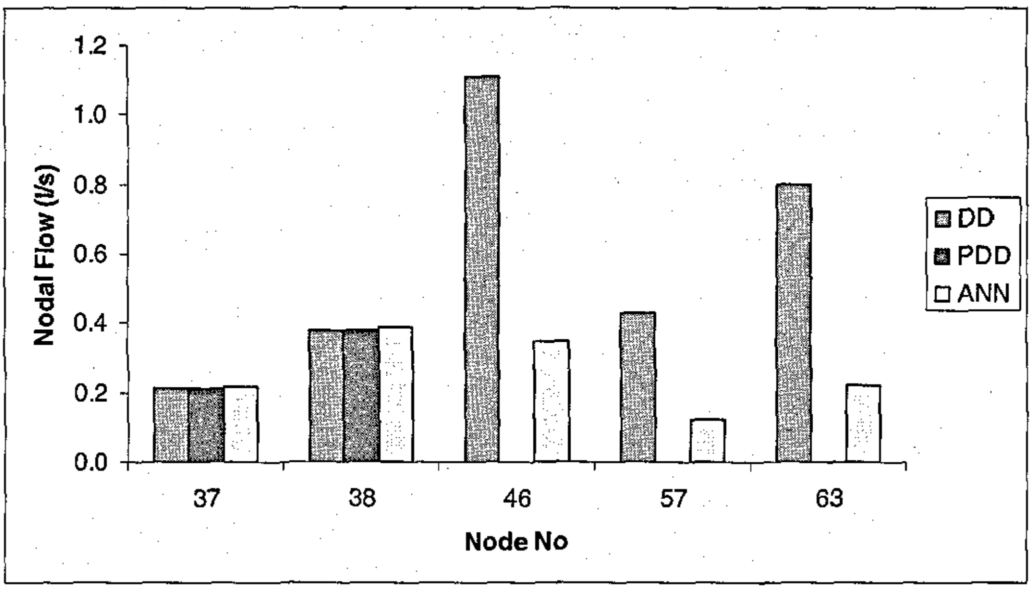


Figure A 3.6 a: Flows at nodes during failure of pipe 46 at 9 am

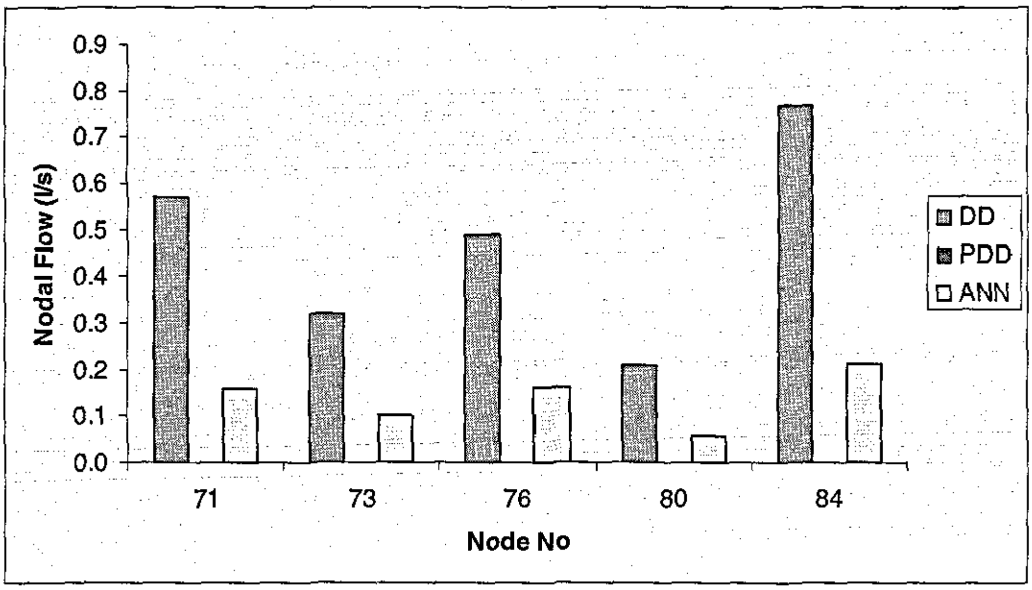


Figure A 3.6 b: Flows at nodes during failure of pipe 46 at 9 am

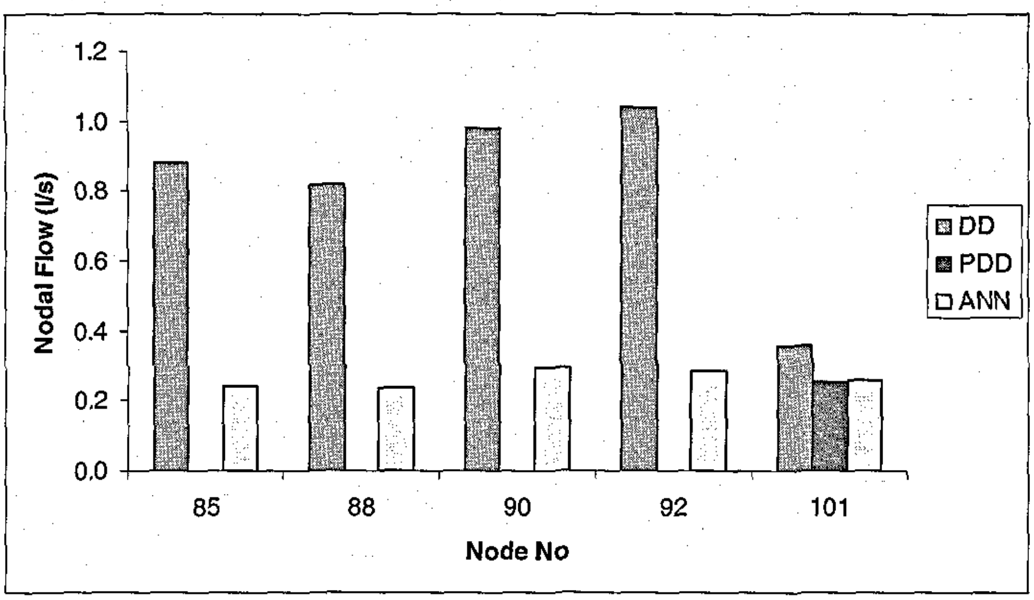


Figure A 3.6 c: Flows at nodes during failure of pipe 46 at 9 am

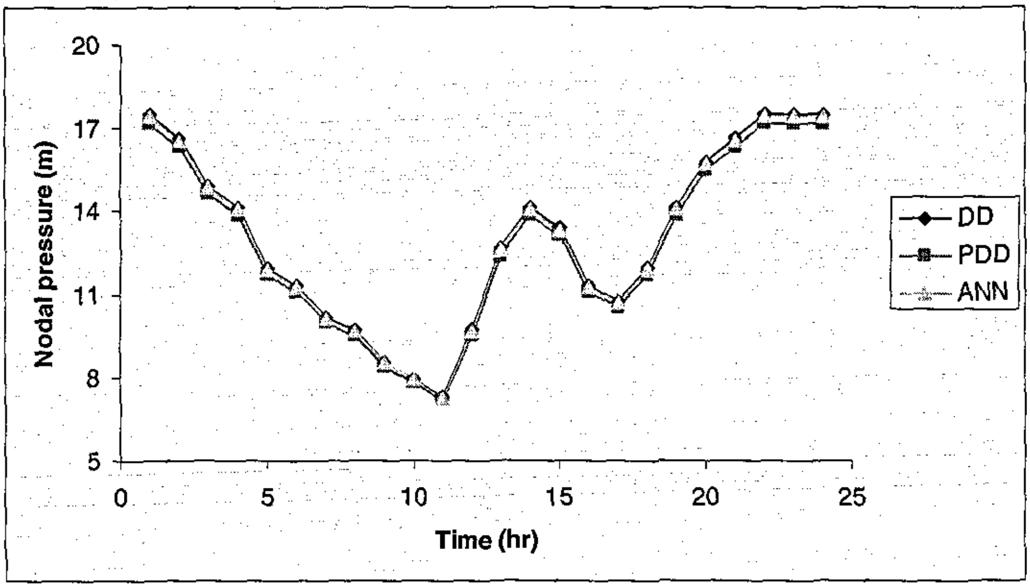


Figure A 3.7 a: Pressure variation at node 17 during failure of pipe 46

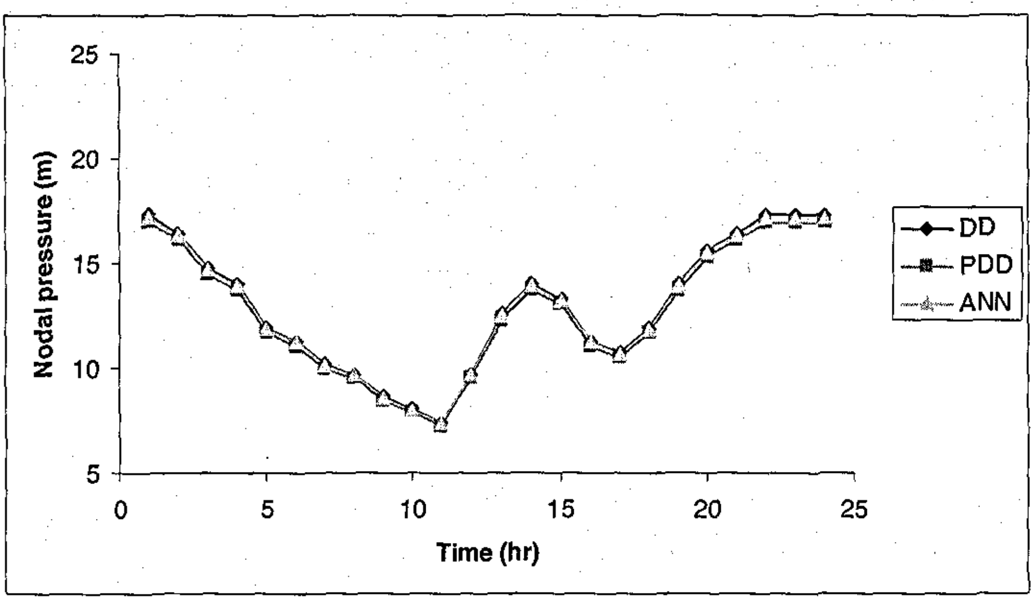


Figure A 3.7 b: Pressure variation at node 71 during failure of pipe 46

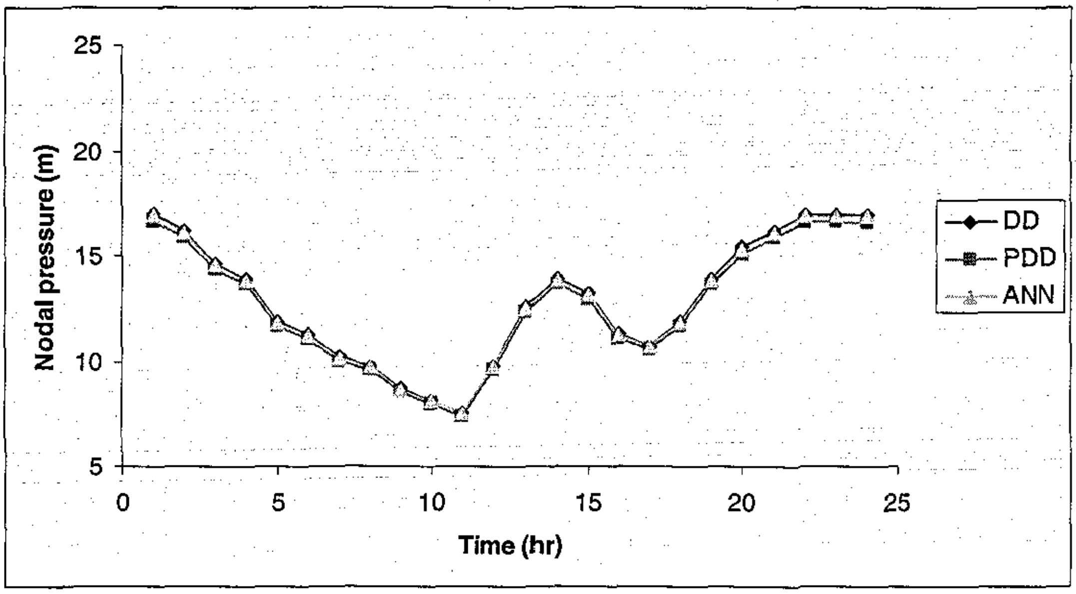


Figure A 3.7 c: Pressure variation at node 85 during failure of pipe 46

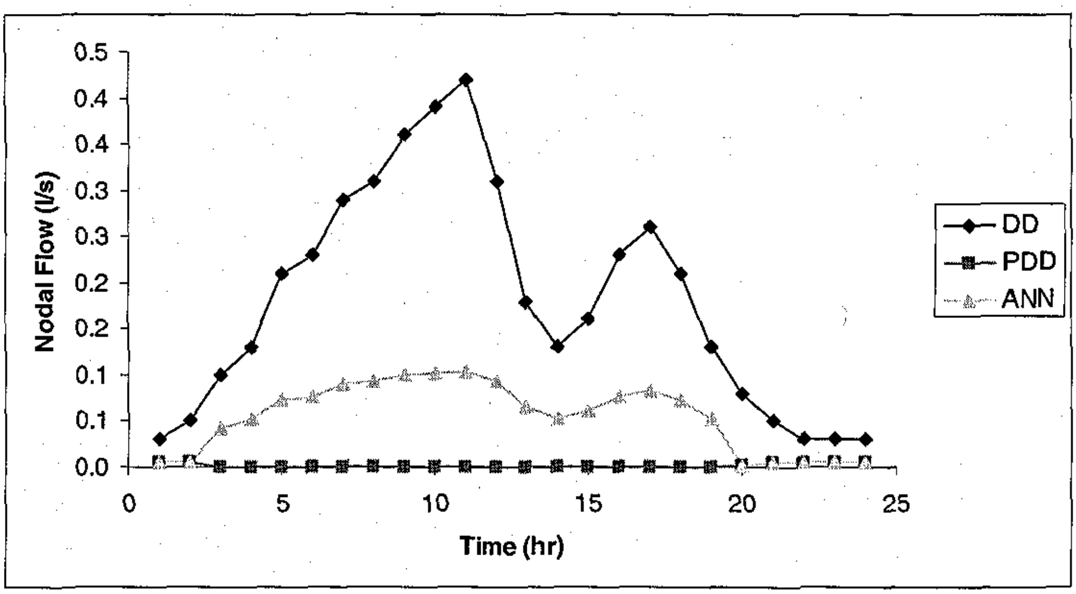


Figure A 3.8 a: Flow variation at node 17 during failure of pipe 46

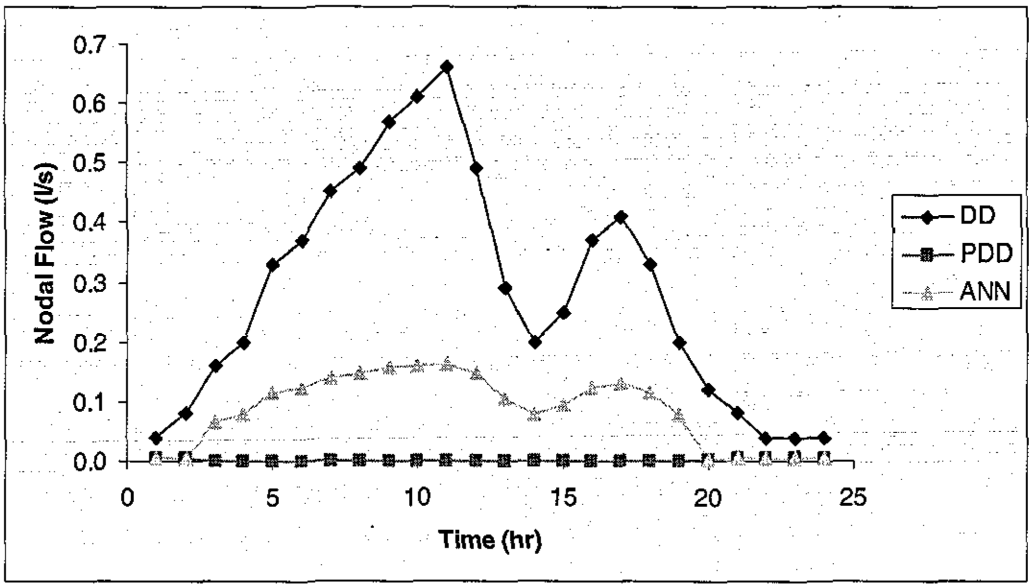


Figure A 3.8 b: Flow variation at node 71 during failure of pipe 46

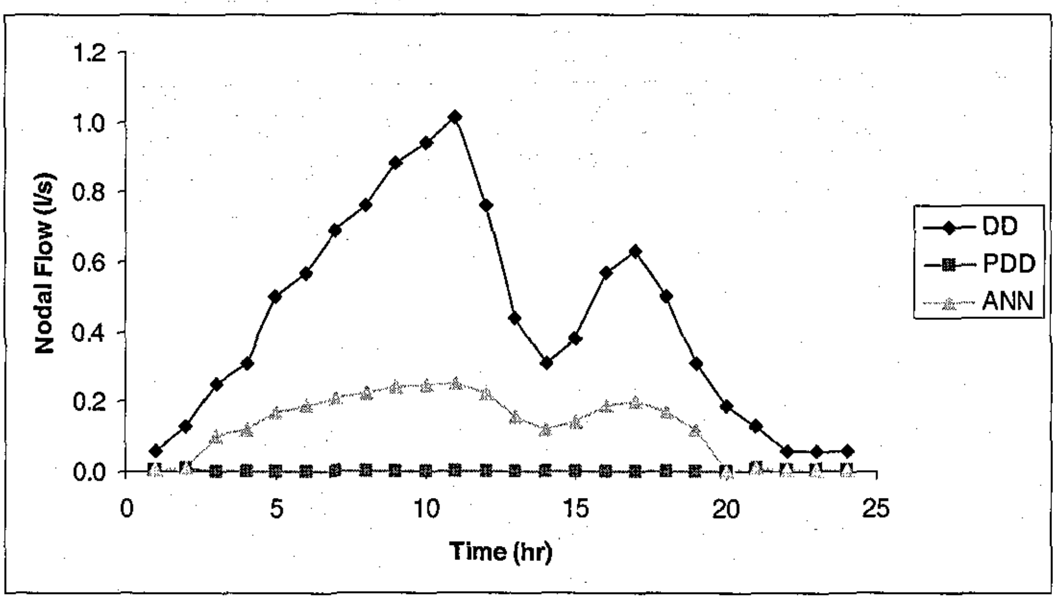


Figure A 3.8 c: Flow variation at node 85 during failure of pipe 46

Table A 3.1: Case study network details

Pipe	Lenght	Dia(mm)	C Val	S_Node	Dem(l/s)	Ele(m)	E_Node	Dem(l/s)	Ele(m)
1	1040	300	100	1	0.73	145	2	0.91	147.5
2	640	300	100	2	0.91	147.5	3	0.83	142.5
3	640	300	100	1	0.73	145	23	1.19	135
4	360	200	100	23	1.19	135	4	0.62	132.5
5	240	300	100	4	0.62	132.5	25	0.4	130
6	272	300	100	4	0.62	132.5	24	1.99	135
7	128	300	100	25	0.4	130	104	1.45	130
8	160	300	100	104	1.45	130	103	1.68	130
9	432	300	100	25	0.4	130	26	1.37	125
10	272	250	100	26	1.37	125	5	1.84	120.5
11	640	250	100	103	1.68	130	102	1.87	125
12	720	300	100	102	1.87	125	44	0.89	130
13	640	300	100	102	1.87	125	43	1.88	120
14	560	300	100	43	1.88	120	5	1.84	120.5
15	640	300	100	3	0.83	142.5	27	0.81	135
16	480	300	100	27	0.81	135	7	1	130
17	752	300	100	7	1	130	6	0.77	140
18	400	300	100	6	0.77	140	5	1.84	120.5
19	480	300	100	3	0.83	142.5	28	0.77	135
20	1152	300	100	28	0.77	135	29	1.21	135
21	560	200	100	7	1	130	40	1.17	125
22	512	100	100	40	1.17	125	9	1.5	125
23	640	100	100	33	1.21	135	8	0.69	132.5
24	208	100	100	8	0.69	132.5	32	1.47	130
25	496	100	100	32	1.47	130	34	0.64	136
26	224	300	100	34	0.64	136	35	1.2	136
27	368	100	100	8	0.69	132.5	31	1.6	130
29	128	300	100	9	1.5	125	10	0.8	125
30	432	300	100	10	0.8	125	39	0.69	130
31	352	300	100	39	0.69	130	11	0.62	125
32	640	300	100	11	0.62	125	37	0.5	120
33	320	300	100	37	0.5	120	12	0.22	115
34	608	100	100	12	0.22	115	36	0.87	120
35	688	100	100	10	0.8	125	42	0.57	125
36	112	200	100	42	0.57	125	101	0.58	120
37	640	100	100	11	0.62	125	41	1	125
38	304	100	100	41	1	125	99	0.42	110
39	192	100	100	99	0.42	110	100	0.56	115
40	672	250	100	100	0.56	115	13	1.23	125
41	416	300	100	44	0.89	130	45	1.52	130
42	560	300	100	45	1.52	130	14	2.48	130
43	624	200	100	14	2.48	130	46	2.3	130
44	576	100	100	46	2.3	130	85	1.84	125
45	1488	300	100	101	0.58	120	85	1.84	125
46	912	300	100	6	0.77	140	13	1.23	125
47	512	300	100	37	0.5	120	97	1.18	120
48	512	300	100	97	1.18	120	38	0.61	115
49	352	300	100	12	0.22	115	38	0.61	115
50	416	100	100	38	0.61	115	95	1.12	115
51	608	300	100	95	1.12	115	65	0.78	105
52	400	300	100	65	0.78	105	89	1.66	110

53	320	100	100	17	0.74	125	51	1.03	105
54	640	100	100	20	1.96	100	76	1.02	100
55	752	200	100	97	1.18	120	96	1.23	115
56	544	300	100	96	1.23	115	90	1.6	105
57	544	100	100	90	1.6	105	65	0.78	105
58	576	100	100	96	1.23	115	95	1.12	115
59	592	250	100	98	1.14	115	96	1.23	115
60	624	250	100	98	1.14	115	99	0.42	110
61	352	300	100	14	2.48	130	47	0.53	130
62	320	300	100	47	0.53	130	84	1.25	0
63	768	300	100	84	1.25	0	15	0.93	0
64	944	300	100	15	0.93	0	83	0.94	125
65	672	300	100	83	0.94	125	48	0.81	0
66	480	200	100	48	0.81	0	84	1.25	0
67	480	300	100	83	0.94	125	69	1.25	130
68	960	300	100	69	1.25	130	71	1.2	125
69	240	300	100	71	1.2	125	67	1.37	125
70	560	300	100	67	1.37	125	70	1.09	125
71	320	200	100	71	1.2	125	72	0.78	125
72	464	300	100	72	0.78	125	73	0.67	130
73	1040	300	100	84	1.25	0	82	1.42	125
74	960	300	100	82	1.42	125	69	1.25	130
75	160	300	100	82	1.42	125	68	1.06	125
76	560	200	100	68	1.06	125	79	0.28	125
77	528	150	100	79	0.28	125	72	0.78	125
78	1200	150	100	84	1.25	0	85	1.84	125
79	480	150	100	85	1.84	125	86	1.71	115
80	192	150	100	86	1.71	115	49	2	115
81	416	300	100	49	2	115	17	0.74	125
82	1000	300	100	17	0.74	125	87	0.44	120
83	512	300	100	87	0.44	120	16	0.64	125
84	160	150	100	17	0.74	125	50	0.9	125
85	528	150	100	16	0.64	125	50	0.9	125
86	352	300	100	16	0.64	125	64	0.61	115
87	928	300	100	64	0.61	115	63	1.64	127
88	640	300	100	63	1.64	127	73	0.67	130
89	448	150	100	79	0.28	125	80	0.5	120
90	320	300	100	80	0.5	120	81	0.46	120
91	1232	300	100	81	0.46	120	86	1.71	115
92	480	300	100	63	1.64	127	22	1.08	130
93	480	300	100	22	1.08	130	74	1.89	127
94	832	300	100	74	1.89	127	75	1.32	125
95	112	300	100	75	1.32	125	56	0.17	105
96	464	300	100	56	0.17	105	76	1.02	100
97	432	300	100	22	1.08	130	61	0.43	125
98	592	300	100	61	0.43	125	60	1.34	110
99	560	300	100	62	0.82	125	21	1.69	105
100	352	300	100	21	1.69	105	59	1.69	105
101	464	300	100	59	1.69	105	60	1.34	110
102	176	300	100	21	1.69	105	58	1.23	105
103	544	300	100	58	1.23	105	75	1.32	125
104	592	150	100	20	1.96	100	88	1.96	100
105	560	300	100	88	1.96	100	65	0.78	105
106	272	300	100	64	0.61	115	78	1.57	115
107	208	300	100	78	1.57	115	77	2.48	110
108	672	100	100	77	2.48	110	74	1.89	127

109	864	100	100	78	1.57	115	22	1.08	130
110	160	100	100	51	1.03	105	52	0.6	105
111	320	300	100	52	0.6	105	18	0.47	105
112	320	300	100	18	0.47	105	53	0.4	105
113	384	150	100	53	0.4	105	54	0.94	105
114	336	100	100	54	0.94	105	55	1.22	130
115	240	100	100	55	1.22	130	75	1.32	125
116	228	300	100	18	0.47	105	19	1.09	110
117	112	300	100	19	1.09	110	94	0.82	105
118	528	300	100	94	0.82	105	93	0.42	100
119	80	150	100	93	0.42	100	57	0.89	100
120	272	100	100	57	0.89	100	76	1.02	100
121	688	100	100	49	2	115	91	1.35	110
122	672	100	100	18	0.47	105	91	1.35	110
123	512	100	100	91	1.35	110	92	1.68	110
124	640	300	100	90	1.6	105	66	1.13	105
125	672	100	100	66	1.13	105	19	1.09	110
126	800	300	100	92	1.68	110	66	1.13	105
127	250	300	100	106		148	3	0.83	142.5
128	500	100	100	30	1.63	135	107	0	0
129	300	100	100	9	150	125	107	0	0
130	660	300	100	107	0	0	31	1.6	130
131	250	300	100	105		135	22	1.08	130
132	1000	100	100	31	0.47	130	39	0.7	127
133	750	150	100	100	0.16	120	92	0.54	115
134	250	300	100	110	Tank	160	3	0.27	142.5
135	Pump			111			110		110
136	250	300	100	112	Tank	157	11	0.17	125
137	Pump			113					112

Tank dimensions:
Tank1 (node 110)
Diameter: 15.5 m
Max level: 8m
Min level: 4m
Elevation: 160m

Tank2 (node 112)
Diameter: 15.5 m
Max level: 8m
Min level: 4m
Elevation: 157m

Pump Curve: $H = 77.3 - 1.8 * 10^{-2} Q^2$

Table A3.2: Pipe failure results for the case study network

Pipe No	Failure1		Failure2		Failure3		Failure4	
	FT(days)	RD(hours)	FT(days)	RD(hours)	FT(days)	RD(hours)	FT(days)	RD(hours)
36	301	59	1690	8	3125	32		
37	2945	40	3468.3	7				
38	946	33	2563.6	71				
39	2989	27						
40	0							
41	648	57						
42	1784.5	24						
43	0							
44	0							
45	0							
46	0							
47	566	49						
48	2013	6						
49	189	66						
50	1969.4	39	3133.4	56				
51	3125.6	53	3603.4	47				
52	245.7	71						
53	1765.9	6						
54	0							
55	548	64						
56	2340	19						
57	0							
58	0							
59	0							
60	102	23	1225	12				
61	2359	35	2432	47				
62	3321	53						
63	0							
64	0							
65	999	43	1112	21				
66	2197	70						
67	671	13	891	19	1790.8	16	3100	30
68	1354	46						
69	1479	72						
70	3441	31						
71	0							
72	0							
73	342	53	567	24				
74	0							
75	116	11	245	9				
76	773	45	877	5				
77	712	23	422	43				
78	0							
79								
80	3115	22	3649	57				
81	111	12	232	41	1452	31	2760	55
82	1160	63	1900	37	3010	48		
83								
84	2289	46	3068	11				
85								

86	209	11	241	13				
87	313	21	639	10	1811	57		
88	631	33	830	44				
89								
90	1030	11	2014	28				
91	1641	59						
92	0							
93	174	33	669	54	774	31		
94	285	27	3019	67				
95	172	11	2213	66				
96	104	6	2102	36	3602	71		
97								
98	901	25	1842	36				
99	918	17						
100								
101								
102	147	44	409	14				
103	114	30	1694	65	2703	41	3477	28
104								
105								
106	181	44	3109	60				
107	106	34	692	23	2017	22		
108	511	36	1771	37	1941	53		
109	593	21						
110	401	33	626	6	1825	45		
111	838	29						
112								
113	0							
114	219	5	1901	55				
115	294	64	622	42	1605	57	3270	22
116	702	6	1944	42				
117	506	24	990	66				
118	3304	44	674	48				
119								
120	0							
121								
122	587	59	749	55	2831	46		
123	850	59	1831	51				
124	708	7	2089	58				
125	601	41	693	55	1101	9		
126	404	10	3403	49				
127								
128	518	46	3005	60				
129								
130	2003	21						
131	2711	67						
132								
133	516	35	1535	33				
134								
135	403	56	1007	46	2571	63		
136	511	40	2517	21	3018	18		

Table A3.3: Secondary network data

Node No	Secondary network Length (m)	No of Branches	Average Demand(l/s)	No of Consumers	Tank Diameter(m)
1	510	3	0.73	316	7.37
2	550	3	0.91	394	8.23
3	580	3	0.83	359	7.86
4	500	3	0.62	268	6.79
5	875	4	1.84	795	11.69
6	525	3	0.77	333	7.57
7	560	3	1	432	8.62
8	505	3	0.69	299	7.17
9	580	4	1.5	648	10.56
10	525	3	0.8	346	7.72
11	500	3	0.62	268	6.79
12	500	3	0.22	96	4.07
13	855	4	1.23	532	9.57
14	1200	5	2.48	1072	13.58
15	595	4	0.93	402	8.32
16	505	3	0.64	277	6.9
17	510	3	0.74	320	7.42
18	510	3	0.47	204	5.93
19	565	5	1.09	471	9
20	1025	4	1.96	847	12.07
21	800	4	1.69	731	11.21
22	565	4	1.08	467	8.96
23	850	4	1.19	515	9.41
24	900	4	1.99	860	12.16
25	505	3	0.4	173	5.46
26	750	4	1.37	592	10.09
27	570	3	0.81	350	7.76
28	515	3	0.77	333	7.57
29	855	4	1.21	523	9.48
30	795	4	1.63	705	11.01
31	580	4	1.6	692	10.91
32	705	4	1.47	636	10.46
33	855	4	1.21	523	9.48
34	500	3	0.64	277	6.9
35	575	3	1.2	519	9.45
36	580	3	0.87	376	8.04
37	510	3	0.5	216	6.1
38	500	3	0.61	264	6.74
39	505	3	0.69	299	7.17
40	840	4	1.17	506	9.33
41	560	3	1	432	8.62
42	500	3	0.57	247	6.52
43	830	4	1.88	813	11.82
44	585	3	0.89	385	8.14
45	900	4	1.52	657	10.63
46	1100	5	2.3	994	13.07
47	500	3	0.53	229	6.28
48	570	3	0.81	350	7.76
49	1200	5	2	864	12.19
50	525	4	0.9	389	8.18

51	560	5	1.03	445	8.75
52	515	3	0.6	260	6.69
53	505	3	0.4	173	5.46
54	600	4	0.94	407	8.37
55	855	4	1.22	528	9.53
56	500	3	0.17	74	3.57
57	585	3	0.89	385	8.14
58	1040	4	1.23	532	9.57
59	800	4	1.69	731	11.21
60	670	5	1.34	579	9.98
61	505	3	0.43	186	5.66
62	570	3	0.82	355	7.81
63	795	5	1.64	709	11.04
64	500	3	0.61	264	6.74
65	530	3	0.78	337	7.61
66	825	4	1.13	489	9.17
67	750	4	1.37	592	10.09
68	565	4	1.06	458	8.88
69	1045	4	1.25	540	9.64
70	570	4	1.09	471	9
71	575	3	1.2	519	9.45
72	530	3	0.78	337	7.61
73	505	3	0.67	290	7.06
74	825	5	1.89	817	11.85
75	665	5	1.32	571	9.91
76	565	3	1.02	441	8.71
77	1200	8	2.48	1072	13.58
78	780	4	1.57	679	10.81
79	500	3	0.28	121	4.56
80	510	3	0.5	216	6.1
81	510	3	0.46	199	5.85
82	755	4	1.42	614	10.28
83	600	4	0.94	407	8.37
84	1045	4	1.25	540	9.64
85	1105	5	1.84	795	11.69
86	810	4	1.71	739	11.27
87	500	3	0.44	191	5.73
88	1195	5	1.96	847	12.07
89	800	4	1.66	718	11.11
90	580	4	1.6	692	10.91
91	745	4	1.35	584	10.02
92	795	4	1.68	726	11.17
93	500	3	0.42	182	5.6
94	570	3	0.82	355	7.81
95	825	4	1.12	484	9.12
96	855	4	1.23	532	9.57
97	1010	4	1.18	510	9.37
98	830	4	1.14	493	9.21
99	500	3	0.42	182	5.6
100	500	3	0.56	242	6.45
101	500	3	0.58	251	6.57
102	820	4	1.87	808	11.79
103	800	4	1.68	726	11.17
104	700	4	1.45	627	10.38

Table A 3.4: Consumer distribution and their corresponding weights for impact and consequence

Node No	Con1	Con2	Care H	Hospitals	Schools	Business	Weights
1	0.55	0.3	0	0	0	0.15	0.33
2	0.55	0.45	0	0	0	0	0.42
3	0.55	0.3	0	0	0	0.15	0.33
4	0.45	0.55	0	0	0	0	0.42
5	0.3	0.3	0	0.4	0	0	0.42
6	0.55	0.1	0	0	0.2	0.15	0.37
7	0.3	0.6	0	0.1	0	0	0.53
8	0.55	0.15	0	0	0	0.3	0.33
9	0.55	0.35	0	0	0	0.1	0.33
10	0.55	0.15	0.3	0	0	0	0.42
11	0.55	0.3	0	0	0	0.15	0.33
12	0.4	0.2	0	0	0.4	0	0.44
13	0.55	0.3	0	0	0	0.15	0.33
14	0.55	0.3	0	0	0	0.15	0.33
15	0.55	0.35	0	0	0	0.1	0.33
16	0.55	0.3	0	0	0	0.15	0.33
17	0.55	0.3	0	0	0	0.15	0.33
18	0.55	0.1	0.3	0	0	0.05	0.33
19	0.55	0.2	0	0	0	0.25	0.33
20	0.55	0.25	0	0	0	0.2	0.33
21	0.55	0.1	0.3	0	0	0.05	0.33
22	0.55	0.3	0	0	0	0.15	0.33
23	0.55	0.3	0	0	0	0.15	0.33
24	0.5	0.5	0	0	0	0	0.42
25	0.45	0.55	0	0	0	0	0.42
26	0.55	0.4	0	0	0	0.05	0.33
27	0.55	0.15	0	0	0.3	0	0.44
28	0.55	0.4	0	0	0	0.05	0.33
29	0.5	0	0.5	0	0	0	0.42
30	0.55	0.4	0	0	0	0.05	0.33
31	0.4	0.3	0	0	0.3	0	0.44
32	0.55	0.3	0	0	0	0.15	0.33
33	0.55	0.25	0	0	0	0.2	0.33
34	0.5	0.1	0.4	0	0	0	0.49
35	0.5	0.5	0	0	0	0	0.42
36	0.55	0.3	0	0	0	0.15	0.33
37	0.55	0	0.4	0	0	0.05	0.33
38	0.55	0.25	0	0	0	0.2	0.33
39	0.55	0.3	0	0	0	0.15	0.33
40	0.5	0.5	0	0	0	0	0.42
41	0.55	0.35	0	0	0	0.1	0.33
42	0.55	0.2	0	0	0	0.25	0.33
43	0.55	0.1	0.3	0	0	0.05	0.41
44	0.5	0.1	0	0	0.4	0	0.44
45	0.4	0.6	0	0	0	0	0.42
46	0.55	0.2	0	0	0	0.25	0.33
47	0.55	0.2	0	0	0	0.25	0.33
48	0.55	0.15	0	0	0	0.3	0.33
49	0.55	0.25	0	0	0	0.2	0.33
50	0.5	0.2	0.3	0	0	0	0.49
51	0.55	0.3	0	0	0	0.15	0.33
52	0.55	0.35	0	0	0	0.1	0.33

53	0.55	0.2	0	0	0	0.25	0.33
54	0.55	0	0	0	0.3	0.15	0.33
55	0.55	0.2	0	0	0	0.25	0.33
56	0.55	0.2	0	0	0	0.25	0.33
57	0.55	0.1	0	0	0	0.35	0.33
58	0.55	0.4	0	0	0	0.05	0.33
59	0.55	0.2	0.2	0	0	0.05	0.42
60	0.5	0.5	0	0	0	0	0.42
61	0.55	0.3	0	0	0	0.15	0.33
62	0.55	0.1	0	0	0	0.35	0.33
63	0.5	0.1	0	0	0.4	0	0.44
64	0.55	0.15	0	0	0	0.3	0.33
65	0.55	0.1	0	0	0	0.35	0.33
66	0.55	0.3	0	0	0	0.15	0.33
67	0.55	0.2	0.2	0	0	0.05	0.45
68	0.55	0.4	0	0	0	0.05	0.33
69	0.55	0.3	0	0	0	0.15	0.33
70	0.55	0.3	0	0	0	0.15	0.33
71	0.55	0.2	0	0	0	0.25	0.33
72	0.55	0.3	0	0	0	0.15	0.33
73	0.55	0.2	0	0	0	0.25	0.33
74	0.55	0.2	0	0	0	0.25	0.33
75	0.55	0	0	0	0	0.45	0.33
76	0.55	0.3	0	0	0	0.15	0.33
77	0.55	0.3	0	0	0	0.15	0.33
78	0.55	0.1	0	0	0	0.35	0.33
79	0.55	0.3	0	0	0	0.15	0.33
80	0.55	0	0	0.3	0	0.15	0.33
81	0.55	0.1	0.2	0	0	0.15	0.33
82	0.55	0.3	0	0	0	0.15	0.33
83	0.55	0.2	0	0	0	0.25	0.33
84	0.55	0.2	0	0	0	0.25	0.33
85	0.55	0.15	0	0	0	0.3	0.33
86	0.55	0.15	0	0	0	0.3	0.33
87	0.55	0.3	0	0	0	0.15	0.33
88	0.4	0.3	0	0	0.3	0	0.49
89	0.55	0.15	0.2	0	0	0.1	0.41
90	0.55	0.4	0	0	0	0.05	0.33
91	0.55	0.25	0	0	0	0.2	0.33
92	0.55	0.1	0	0	0	0.35	0.33
93	0.55	0.2	0	0	0	0.25	0.33
94	0.55	0.2	0	0	0	0.25	0.33
95	0.55	0.1	0	0	0	0.35	0.33
96	0.55	0	0	0	0	0.45	0.33
97	0.55	0	0.4	0	0	0.05	0.33
98	0.55	0.2	0.2	0	0	0.05	0.45
99	0.5	0.5	0	0	0	0	0.42
100	0.55	0.35	0	0	0	0.1	0.33
101	0.55	0.4	0	0	0	0.05	0.33
102	0.35	0.65	0	0	0	0	0.42
103	0.3	0.25	0.45	0	0	0	0.52
104	0.55	0.45	0	0	0	0	0.42

Con1- Household with storage, Con2-Household without storage

Table A3.5a: Tables of performance measure (adequacy) calculated

Pipe	1	1	1	4	4	5	7
Node	F2	F3	F4	F2	F3	F1	F1
1	0.286	0.375	0.343	0.570	0.670	0.417	0.526
2	0.246	0.340	0.307	0.528	0.635	0.384	0.523
3	0.230	0.326	0.292	0.512	0.622	0.370	0.523
4	0.172	0.276	0.239	0.452	0.576	0.366	0.478
5	0.282	0.371	0.340	0.563	0.662	0.412	0.550
6	0.198	0.298	0.263	0.489	0.604	0.360	0.577
7	0.214	0.313	0.278	0.504	0.616	0.369	0.543
8	0.157	0.263	0.225	0.434	0.561	0.311	0.513
9	0.000	0.115	0.069	0.245	0.411	0.173	0.411
10	0.184	0.286	0.250	0.459	0.580	0.332	0.481
11	0.076	0.191	0.150	0.353	0.496	0.244	0.412
12	0.000	0.000	0.000	0.000	0.179	0.000	0.188
13	0.227	0.324	0.289	0.509	0.620	0.378	0.528
14	0.313	0.399	0.369	0.594	0.687	0.438	0.569
15	0.229	0.325	0.291	0.508	0.619	0.369	0.521
16	0.113	0.224	0.184	0.405	0.538	0.293	0.470
17	0.162	0.267	0.230	0.432	0.558	0.331	0.483
18	0.000	0.101	0.056	0.240	0.407	0.187	0.394
19	0.226	0.323	0.289	0.503	0.615	0.377	0.517
20	0.282	0.371	0.340	0.563	0.662	0.419	0.555
21	0.271	0.362	0.330	0.550	0.652	0.404	0.543
22	0.229	0.325	0.291	0.508	0.619	0.381	0.531
23	0.273	0.364	0.332	0.561	0.661	0.427	0.532
24	0.314	0.399	0.369	0.604	0.695	0.461	0.564
25	0.000	0.097	0.051	0.250	0.416	0.188	0.403
26	0.264	0.356	0.324	0.545	0.648	0.398	0.541
27	0.199	0.299	0.264	0.482	0.598	0.345	0.531
28	0.199	0.299	0.263	0.476	0.593	0.329	0.492
29	0.266	0.357	0.325	0.543	0.647	0.399	0.534
30	0.268	0.359	0.327	0.551	0.653	0.409	0.555
31	0.274	0.364	0.332	0.556	0.657	0.406	0.559
32	0.264	0.356	0.324	0.545	0.648	0.398	0.548
33	0.258	0.351	0.318	0.549	0.651	0.403	0.563
34	0.197	0.298	0.262	0.461	0.582	0.344	0.536
35	0.259	0.352	0.319	0.546	0.649	0.404	0.564
36	0.151	0.258	0.220	0.438	0.563	0.306	0.460
37	0.000	0.116	0.071	0.268	0.429	0.173	0.357
38	0.096	0.209	0.169	0.372	0.511	0.261	0.425
39	0.136	0.244	0.206	0.413	0.543	0.293	0.450
40	0.227	0.324	0.289	0.509	0.620	0.368	0.537
41	0.187	0.289	0.253	0.476	0.594	0.335	0.483
42	0.113	0.224	0.184	0.382	0.519	0.274	0.438
43	0.279	0.369	0.337	0.565	0.664	0.417	0.548
44	0.229	0.325	0.291	0.504	0.616	0.369	0.522
45	0.278	0.368	0.336	0.561	0.661	0.409	0.548
46	0.309	0.396	0.365	0.586	0.680	0.435	0.566
47	0.126	0.235	0.196	0.379	0.517	0.286	0.467
48	0.167	0.271	0.234	0.448	0.571	0.333	0.497
49	0.276	0.366	0.334	0.560	0.660	0.414	0.545
50	0.202	0.302	0.266	0.491	0.606	0.360	0.515
51	0.202	0.302	0.267	0.481	0.598	0.360	0.504

52	0.107	0.219	0.179	0.392	0.528	0.290	0.451
53	0.005	0.130	0.085	0.274	0.434	0.187	0.394
54	0.173	0.277	0.240	0.458	0.579	0.337	0.487
55	0.266	0.357	0.325	0.543	0.647	0.399	0.542
56	0.000	0.000	0.000	0.000	0.000	0.000	0.088
57	0.170	0.274	0.237	0.445	0.569	0.335	0.486
58	0.245	0.339	0.306	0.525	0.632	0.382	0.528
59	0.258	0.351	0.318	0.537	0.641	0.401	0.535
60	0.245	0.340	0.306	0.522	0.630	0.383	0.529
61	0.000	0.115	0.069	0.245	0.411	0.173	0.385
62	0.201	0.300	0.265	0.476	0.593	0.346	0.505
63	0.272	0.363	0.331	0.557	0.658	0.412	0.551
64	0.118	0.228	0.189	0.394	0.529	0.279	0.456
65	0.130	0.239	0.200	0.405	0.537	0.304	0.462
66	0.226	0.323	0.288	0.507	0.618	0.376	0.517
67	0.264	0.356	0.324	0.545	0.648	0.398	0.541
68	0.249	0.343	0.310	0.523	0.631	0.386	0.532
69	0.248	0.342	0.309	0.526	0.633	0.395	0.540
70	0.228	0.324	0.290	0.502	0.614	0.379	0.520
71	0.249	0.343	0.310	0.523	0.631	0.386	0.532
72	0.165	0.269	0.232	0.440	0.565	0.332	0.497
73	0.157	0.263	0.225	0.434	0.561	0.329	0.497
74	0.294	0.382	0.351	0.572	0.669	0.422	0.557
75	0.245	0.340	0.306	0.534	0.639	0.392	0.537
76	0.202	0.302	0.267	0.481	0.598	0.360	0.504
77	0.297	0.385	0.353	0.582	0.678	0.430	0.564
78	0.258	0.351	0.318	0.537	0.641	0.393	0.535
80	0.020	0.143	0.099	0.299	0.454	0.199	0.402
81	0.020	0.143	0.099	0.299	0.454	0.199	0.402
82	0.263	0.355	0.322	0.537	0.641	0.397	0.540
83	0.202	0.301	0.266	0.487	0.602	0.360	0.516
84	0.264	0.356	0.324	0.545	0.648	0.398	0.541
85	0.282	0.371	0.340	0.563	0.662	0.419	0.555
86	0.270	0.361	0.329	0.551	0.653	0.403	0.543
87	0.020	0.143	0.099	0.299	0.454	0.199	0.402
88	0.277	0.367	0.335	0.559	0.659	0.415	0.546
89	0.256	0.349	0.316	0.540	0.644	0.399	0.534
90	0.284	0.374	0.342	0.560	0.660	0.415	0.551
91	0.245	0.339	0.306	0.525	0.632	0.391	0.528
92	0.280	0.370	0.338	0.556	0.656	0.411	0.549
93	0.000	0.057	0.009	0.177	0.357	0.149	0.344
94	0.170	0.274	0.237	0.445	0.569	0.335	0.486
95	0.214	0.313	0.278	0.488	0.603	0.357	0.500
96	0.236	0.332	0.298	0.514	0.623	0.375	0.514
97	0.235	0.331	0.297	0.508	0.618	0.374	0.513
98	0.214	0.313	0.278	0.492	0.606	0.357	0.500
99	0.000	0.116	0.071	0.268	0.429	0.173	0.357
100	0.045	0.164	0.122	0.313	0.464	0.219	0.395
101	0.090	0.204	0.164	0.382	0.519	0.256	0.438
102	0.280	0.370	0.338	0.564	0.663	0.418	0.554
103	0.295	0.383	0.352	0.579	0.675	0.430	0.558
104	0.272	0.363	0.331	0.549	0.651	0.405	0.546
AD	0.807	0.711	0.745	0.537	0.419	0.660	0.505
Equity	0.888	0.898	0.900	0.833	0.928	0.594	0.829
$NSR_{95,i}$	0.173	0.048	0.135	0.029	0.010	0.029	0.010

Table A3.5b: Tables of performance measure (adequacy) calculated

Pipe	9	9	10	11	11	12	13
Node	**F1**	**F2**	**F2**	**F1**	**F2**	**F1**	**F2**
1	0.573	0.451	0.167	0.167	0.167	0.150	0.333
2	0.572	0.449	0.183	0.167	0.167	0.150	0.333
3	0.572	0.449	0.183	0.167	0.167	0.167	0.348
4	0.515	0.375	0.046	0.020	0.020	0.026	0.239
5	0.605	0.492	0.238	0.230	0.230	0.214	0.384
6	0.588	0.469	0.149	0.129	0.129	0.132	0.321
7	0.588	0.470	0.182	0.167	0.167	0.150	0.333
8	0.606	0.491	0.261	0.822	0.822	0.088	0.286
9	0.500	0.354	0.074	0.000	0.000	0.000	0.144
10	0.546	0.416	0.135	0.135	0.135	0.204	0.368
11	0.485	0.338	0.020	0.020	0.020	0.026	0.261
12	0.289	0.086	0.000	0.000	0.000	0.000	0.000
13	0.585	0.465	0.180	0.167	0.167	0.163	0.345
14	0.622	0.513	0.265	0.259	0.259	0.251	0.413
15	0.579	0.458	0.167	0.167	0.167	0.150	0.346
16	0.520	0.382	0.058	0.035	0.035	0.039	0.269
17	0.545	0.415	0.111	0.091	0.091	0.093	0.290
18	0.447	0.288	0.000	0.000	0.000	0.000	0.158
19	0.576	0.455	0.179	0.167	0.167	0.163	0.344
20	0.605	0.492	0.238	0.230	0.230	0.223	0.398
21	0.594	0.478	0.218	0.218	0.218	0.202	0.382
22	0.579	0.458	0.181	0.167	0.167	0.165	0.346
23	0.589	0.471	0.203	0.190	0.190	0.187	0.363
24	0.618	0.509	0.265	0.258	0.258	0.243	0.406
25	0.449	0.290	0.000	0.000	0.000	0.000	0.126
26	0.592	0.475	0.199	0.188	0.188	0.183	0.360
27	0.565	0.440	0.150	0.132	0.132	0.115	0.306
28	0.554	0.427	0.130	0.130	0.130	0.113	0.304
29	0.591	0.474	0.209	0.209	0.209	0.194	0.368
30	0.621	0.511	0.304	0.234	0.234	0.218	0.388
31	0.617	0.507	0.296	0.267	0.267	0.214	0.384
32	0.616	0.505	0.297	0.556	0.556	0.204	0.376
33	0.635	0.530	0.312	0.623	0.623	0.210	0.381
34	0.637	0.530	0.296	0.831	0.831	0.131	0.320
35	0.638	0.532	0.316	0.625	0.625	0.211	0.383
36	0.528	0.393	0.100	0.100	0.100	0.100	0.311
37	0.438	0.277	0.000	0.000	0.000	0.000	0.198
38	0.497	0.353	0.042	0.042	0.042	0.045	0.272
39	0.519	0.381	0.083	0.083	0.083	0.133	0.403
40	0.599	0.483	0.193	0.167	0.167	0.163	0.345
41	0.547	0.418	0.138	0.138	0.138	0.136	0.337
43	0.603	0.490	0.235	0.227	0.227	0.212	0.389
44	0.580	0.459	0.182	0.167	0.167	0.150	0.347
45	0.604	0.490	0.234	0.223	0.223	0.208	0.388
46	0.619	0.510	0.260	0.254	0.254	0.246	0.409
47	0.529	0.393	0.046	0.020	0.020	0.026	0.239
48	0.547	0.417	0.116	0.097	0.097	0.098	0.294
49	0.601	0.487	0.232	0.224	0.224	0.216	0.386
50	0.565	0.440	0.153	0.138	0.138	0.136	0.337
51	0.565	0.440	0.154	0.139	0.139	0.137	0.324
52	0.517	0.378	0.052	0.028	0.028	0.033	0.244

53	0.466	0.313	0.000	0.000	0.000	0.000	0.158
54	0.549	0.420	0.123	0.107	0.107	0.105	0.300
55	0.598	0.482	0.221	0.209	0.209	0.205	0.377
56	0.138	0.000	0.000	0.000	0.000	0.000	0.000
57	0.548	0.418	0.120	0.103	0.103	0.102	0.297
58	0.586	0.467	0.199	0.188	0.188	0.183	0.360
59	0.592	0.476	0.213	0.203	0.203	0.197	0.371
60	0.587	0.468	0.199	0.188	0.188	0.183	0.360
61	0.458	0.302	0.000	0.000	0.000	0.000	0.144
62	0.565	0.440	0.135	0.135	0.135	0.135	0.323
63	0.600	0.486	0.228	0.219	0.219	0.213	0.391
64	0.522	0.384	0.042	0.042	0.042	0.023	0.253
65	0.527	0.391	0.077	0.058	0.058	0.059	0.280
66	0.576	0.454	0.179	0.167	0.167	0.162	0.344
67	0.597	0.481	0.208	0.208	0.208	0.193	0.376
68	0.589	0.471	0.190	0.190	0.190	0.174	0.363
69	0.589	0.470	0.202	0.190	0.190	0.186	0.363
70	0.578	0.457	0.181	0.167	0.167	0.164	0.345
71	0.589	0.471	0.190	0.190	0.190	0.174	0.363
72	0.546	0.416	0.114	0.094	0.094	0.096	0.292
73	0.544	0.413	0.106	0.083	0.083	0.088	0.286
74	0.611	0.500	0.242	0.242	0.242	0.227	0.401
75	0.587	0.468	0.199	0.188	0.188	0.183	0.370
76	0.565	0.440	0.154	0.139	0.139	0.137	0.324
77	0.612	0.501	0.254	0.248	0.248	0.239	0.409
78	0.592	0.476	0.213	0.203	0.203	0.197	0.371
79	0.352	0.164	0.000	0.000	0.000	0.000	0.000
80	0.473	0.321	0.000	0.000	0.000	0.000	0.171
81	0.473	0.321	0.000	0.000	0.000	0.000	0.171
82	0.596	0.480	0.207	0.207	0.207	0.191	0.375
83	0.565	0.440	0.153	0.137	0.137	0.136	0.323
84	0.597	0.481	0.208	0.208	0.208	0.193	0.376
85	0.605	0.492	0.238	0.230	0.230	0.223	0.391
86	0.599	0.484	0.217	0.217	0.217	0.201	0.381
87	0.473	0.321	0.000	0.000	0.000	0.000	0.171
88	0.602	0.488	0.233	0.225	0.225	0.218	0.387
89	0.591	0.474	0.211	0.201	0.201	0.195	0.377
90	0.602	0.488	0.232	0.232	0.232	0.217	0.393
91	0.586	0.467	0.199	0.188	0.188	0.183	0.360
92	0.600	0.485	0.228	0.228	0.228	0.213	0.390
93	0.422	0.255	0.000	0.000	0.000	0.000	0.088
94	0.548	0.418	0.120	0.103	0.103	0.102	0.297
95	0.563	0.438	0.167	0.167	0.167	0.164	0.358
96	0.575	0.453	0.190	0.190	0.190	0.174	0.373
97	0.574	0.452	0.189	0.189	0.189	0.184	0.371
98	0.563	0.438	0.167	0.167	0.167	0.164	0.357
99	0.438	0.277	0.000	0.000	0.000	0.000	0.198
100	0.469	0.316	0.000	0.000	0.000	0.000	0.215
101	0.507	0.365	0.035	0.035	0.035	0.087	0.289
102	0.604	0.491	0.237	0.228	0.228	0.221	0.390
103	0.612	0.501	0.252	0.244	0.244	0.229	0.395
104	0.601	0.487	0.217	0.206	0.206	0.201	0.374
AD	0.445	0.572	0.844	0.834	0.834	0.863	0.684
Equity	0.914	0.727	0.315	0.316	0.316	0.286	0.557
$NSR_{95,i}$	0.000	0.019	0.260	0.298	0.298	0.298	0.038

Table A3.5c: Tables of performance measures (adequacy) calculated

Pipe	14	14	14	15	15	15	16
Node	F1	F2	F3	F1	F2	F3	F1
1	0.350	0.375	0.167	0.550	0.167	0.313	0.267
2	0.350	0.375	0.183	0.550	0.167	0.313	0.265
3	0.363	0.387	0.183	0.550	0.167	0.313	0.265
4	0.256	0.283	0.046	0.485	0.046	0.213	0.165
5	0.399	0.422	0.238	0.584	0.230	0.364	0.322
6	0.336	0.361	0.149	0.541	0.149	0.298	0.270
7	0.350	0.375	0.182	0.550	0.167	0.313	0.264
8	0.303	0.328	0.261	0.518	0.106	0.263	0.195
9	0.133	0.167	0.074	0.400	0.000	0.083	0.033
10	0.338	0.363	0.135	0.542	0.152	0.300	0.221
11	0.276	0.301	0.020	0.485	0.046	0.213	0.118
12	0.119	0.141	0.000	0.425	0.000	0.117	0.000
13	0.360	0.384	0.180	0.557	0.180	0.324	0.297
14	0.432	0.453	0.265	0.603	0.265	0.394	0.344
15	0.362	0.385	0.167	0.558	0.181	0.325	0.263
16	0.284	0.309	0.058	0.505	0.082	0.243	0.174
17	0.307	0.332	0.111	0.520	0.111	0.267	0.218
18	0.177	0.207	0.000	0.431	0.000	0.130	0.050
19	0.369	0.392	0.179	0.564	0.191	0.333	0.272
20	0.412	0.434	0.238	0.593	0.246	0.379	0.322
21	0.397	0.420	0.218	0.583	0.227	0.362	0.304
22	0.373	0.396	0.181	0.558	0.181	0.325	0.277
23	0.379	0.402	0.203	0.570	0.203	0.343	0.294
24	0.421	0.443	0.265	0.599	0.258	0.388	0.345
25	0.145	0.176	0.000	0.386	0.000	0.063	0.050
26	0.383	0.406	0.199	0.568	0.199	0.339	0.289
27	0.323	0.349	0.150	0.531	0.132	0.284	0.235
28	0.322	0.348	0.130	0.530	0.130	0.283	0.217
29	0.383	0.407	0.209	0.573	0.209	0.348	0.299
30	0.394	0.418	0.304	0.581	0.223	0.359	0.310
31	0.399	0.422	0.296	0.584	0.229	0.364	0.315
32	0.391	0.414	0.297	0.573	0.208	0.347	0.298
33	0.386	0.410	0.312	0.575	0.213	0.351	0.303
34	0.319	0.345	0.296	0.529	0.127	0.280	0.233
35	0.387	0.411	0.316	0.576	0.214	0.352	0.304
36	0.368	0.388	0.100	0.584	0.224	0.363	0.190
37	0.289	0.308	0.000	0.511	0.087	0.250	0.036
38	0.358	0.375	0.042	0.570	0.197	0.341	0.138
39	0.320	0.344	0.083	0.518	0.106	0.263	0.175
40	0.360	0.384	0.193	0.557	0.180	0.324	0.262
41	0.352	0.375	0.138	0.543	0.153	0.302	0.224
42	0.284	0.309	0.058	0.492	0.058	0.224	0.153
43	0.404	0.426	0.235	0.583	0.227	0.363	0.319
44	0.362	0.386	0.182	0.550	0.167	0.313	0.278
45	0.402	0.425	0.234	0.586	0.234	0.368	0.319
46	0.428	0.450	0.260	0.601	0.260	0.390	0.340
47	0.276	0.301	0.046	0.485	0.046	0.213	0.165
48	0.325	0.349	0.116	0.523	0.116	0.271	0.221
49	0.412	0.434	0.232	0.590	0.239	0.373	0.316
50	0.352	0.375	0.153	0.552	0.169	0.315	0.252
51	0.352	0.375	0.154	0.543	0.154	0.302	0.252

52	0.281	0.306	0.052	0.489	0.052	0.219	0.169
53	0.177	0.207	0.000	0.431	0.000	0.130	0.050
54	0.339	0.364	0.123	0.536	0.139	0.290	0.225
55	0.392	0.415	0.221	0.579	0.221	0.357	0.309
56	0.000	0.000	0.000	0.110	0.000	0.000	0.000
57	0.327	0.351	0.120	0.525	0.120	0.274	0.223
58	0.375	0.398	0.199	0.568	0.199	0.339	0.289
59	0.393	0.416	0.213	0.575	0.213	0.351	0.300
60	0.376	0.399	0.199	0.568	0.199	0.340	0.290
61	0.192	0.219	0.000	0.421	0.000	0.115	0.067
62	0.338	0.363	0.135	0.542	0.152	0.300	0.252
63	0.405	0.427	0.228	0.589	0.237	0.371	0.314
64	0.270	0.297	0.042	0.495	0.064	0.228	0.158
65	0.309	0.334	0.077	0.513	0.097	0.255	0.187
66	0.369	0.392	0.179	0.557	0.179	0.323	0.272
67	0.391	0.414	0.208	0.579	0.219	0.356	0.298
68	0.379	0.402	0.190	0.570	0.203	0.343	0.283
69	0.388	0.410	0.202	0.569	0.202	0.342	0.293
70	0.361	0.385	0.181	0.558	0.181	0.324	0.275
71	0.379	0.402	0.190	0.570	0.203	0.343	0.283
72	0.324	0.348	0.114	0.522	0.114	0.269	0.220
73	0.320	0.344	0.106	0.518	0.106	0.263	0.215
74	0.415	0.438	0.242	0.595	0.251	0.382	0.333
75	0.385	0.407	0.199	0.574	0.211	0.349	0.290
76	0.352	0.375	0.154	0.552	0.169	0.315	0.252
77	0.427	0.449	0.254	0.601	0.260	0.390	0.334
78	0.386	0.409	0.213	0.575	0.213	0.351	0.300
79	0.031	0.063	0.000	0.300	0.000	0.000	0.000
80	0.189	0.219	0.000	0.439	0.000	0.143	0.093
81	0.189	0.219	0.000	0.439	0.000	0.143	0.093
82	0.390	0.413	0.207	0.578	0.218	0.355	0.306
83	0.339	0.364	0.153	0.543	0.153	0.301	0.252
84	0.391	0.414	0.208	0.579	0.219	0.356	0.298
85	0.406	0.428	0.238	0.589	0.238	0.371	0.322
86	0.396	0.419	0.217	0.582	0.226	0.361	0.303
87	0.189	0.219	0.000	0.439	0.000	0.143	0.093
88	0.408	0.430	0.233	0.590	0.241	0.374	0.317
89	0.398	0.421	0.211	0.579	0.220	0.357	0.298
90	0.408	0.430	0.232	0.590	0.241	0.374	0.317
91	0.375	0.398	0.199	0.568	0.199	0.339	0.289
92	0.405	0.427	0.228	0.588	0.237	0.370	0.313
93	0.138	0.167	0.000	0.383	0.000	0.057	0.004
94	0.327	0.351	0.120	0.525	0.120	0.274	0.223
95	0.427	0.443	0.167	0.613	0.278	0.406	0.250
96	0.417	0.436	0.190	0.604	0.264	0.394	0.271
98	0.382	0.403	0.167	0.565	0.194	0.335	0.250
99	0.214	0.241	0.000	0.439	0.000	0.143	0.036
100	0.231	0.258	0.000	0.453	0.000	0.164	0.088
101	0.266	0.293	0.035	0.492	0.058	0.224	0.153
102	0.405	0.427	0.237	0.588	0.237	0.370	0.320
103	0.410	0.433	0.252	0.592	0.244	0.376	0.334
104	0.389	0.412	0.217	0.577	0.217	0.354	0.305
AD	0.664	0.641	0.844	0.464	0.843	0.705	0.766
Equity	0.588	0.623	0.851	0.891	0.316	0.525	0.433
$NSR_{95,l}$	0.000	0.019	0.077	0.000	0.231	0.048	0.144

Table A3.5d: Tables of performance measures (adequacy) calculated

Pipe	17	17	18	19	20	21	21
Node	F1	F2	F1	F1	F1	F1	F2
1	0.450	0.167	0.400	0.450	0.350	0.600	0.167
2	0.450	0.167	0.400	0.450	0.350	0.600	0.167
3	0.450	0.167	0.400	0.450	0.350	0.600	0.167
4	0.371	0.046	0.315	0.374	0.259	0.544	0.046
5	0.492	0.230	0.445	0.492	0.399	0.630	0.230
6	0.439	0.149	0.389	0.441	0.339	0.582	0.129
7	0.450	0.167	0.400	0.450	0.350	0.600	0.167
8	0.410	0.106	0.358	0.395	0.285	0.573	0.106
9	0.267	0.000	0.200	0.267	0.133	0.467	0.000
10	0.440	0.152	0.377	0.429	0.325	0.585	0.135
11	0.371	0.046	0.315	0.353	0.235	0.529	0.020
12	0.256	0.000	0.156	0.106	0.000	0.413	0.000
13	0.459	0.180	0.410	0.460	0.362	0.607	0.180
14	0.515	0.265	0.472	0.526	0.439	0.648	0.265
15	0.460	0.181	0.412	0.485	0.377	0.608	0.181
16	0.395	0.082	0.342	0.455	0.332	0.563	0.082
17	0.414	0.111	0.361	0.464	0.345	0.575	0.111
18	0.304	0.000	0.242	0.362	0.212	0.496	0.000
19	0.467	0.191	0.410	0.489	0.383	0.607	0.179
20	0.503	0.246	0.458	0.544	0.437	0.640	0.246
21	0.490	0.227	0.444	0.505	0.414	0.630	0.227
22	0.460	0.181	0.412	0.532	0.403	0.608	0.181
23	0.474	0.203	0.427	0.476	0.380	0.611	0.190
24	0.510	0.258	0.466	0.510	0.421	0.644	0.258
25	0.250	0.000	0.182	0.282	0.114	0.455	0.000
26	0.471	0.199	0.424	0.473	0.376	0.616	0.199
27	0.427	0.132	0.375	0.427	0.323	0.583	0.132
28	0.426	0.130	0.374	0.426	0.322	0.583	0.130
29	0.478	0.209	0.431	0.478	0.383	0.621	0.209
30	0.488	0.223	0.441	0.488	0.394	0.627	0.223
31	0.491	0.229	0.446	0.493	0.400	0.631	0.229
32	0.478	0.208	0.430	0.478	0.383	0.620	0.208
33	0.481	0.213	0.433	0.481	0.386	0.622	0.213
34	0.424	0.127	0.371	0.424	0.319	0.581	0.127
35	0.481	0.214	0.434	0.481	0.387	0.623	0.214
36	0.454	0.171	0.408	0.406	0.298	0.588	0.136
37	0.379	0.056	0.304	0.293	0.164	0.521	0.000
38	0.443	0.153	0.398	0.368	0.253	0.578	0.108
39	0.410	0.106	0.358	0.395	0.285	0.560	0.083
40	0.459	0.180	0.410	0.460	0.350	0.600	0.167
41	0.441	0.153	0.391	0.431	0.328	0.595	0.153
42	0.379	0.058	0.324	0.382	0.268	0.550	0.058
43	0.490	0.227	0.444	0.496	0.405	0.629	0.227
45	0.494	0.234	0.449	0.503	0.413	0.633	0.234
46	0.512	0.260	0.468	0.523	0.436	0.646	0.260
47	0.371	0.046	0.315	0.415	0.306	0.544	0.046
48	0.417	0.116	0.365	0.448	0.346	0.577	0.116
49	0.498	0.239	0.453	0.512	0.416	0.632	0.232
50	0.452	0.169	0.403	0.491	0.383	0.603	0.169
51	0.442	0.154	0.392	0.478	0.368	0.595	0.154
52	0.375	0.052	0.319	0.436	0.308	0.547	0.052

53	0.304	0.000	0.242	0.388	0.242	0.496	0.000
54	0.432	0.139	0.382	0.461	0.346	0.580	0.123
55	0.486	0.221	0.440	0.550	0.424	0.627	0.221
56	0.000	0.000	0.000	0.140	0.000	0.220	0.000
57	0.419	0.120	0.367	0.462	0.346	0.579	0.120
58	0.471	0.199	0.424	0.499	0.396	0.616	0.199
59	0.480	0.213	0.434	0.504	0.404	0.623	0.213
60	0.472	0.199	0.424	0.500	0.397	0.617	0.199
61	0.292	0.000	0.229	0.413	0.233	0.488	0.000
62	0.440	0.152	0.390	0.496	0.371	0.594	0.152
63	0.497	0.237	0.452	0.521	0.424	0.630	0.228
64	0.383	0.064	0.328	0.420	0.313	0.553	0.064
65	0.404	0.097	0.352	0.439	0.335	0.570	0.097
66	0.458	0.179	0.409	0.488	0.393	0.607	0.179
67	0.485	0.219	0.439	0.504	0.403	0.626	0.219
68	0.474	0.203	0.427	0.496	0.391	0.619	0.203
69	0.474	0.202	0.426	0.504	0.401	0.618	0.202
70	0.459	0.181	0.411	0.494	0.388	0.608	0.181
71	0.474	0.203	0.427	0.496	0.391	0.619	0.203
72	0.415	0.114	0.363	0.463	0.346	0.576	0.114
73	0.410	0.106	0.358	0.483	0.345	0.573	0.106
74	0.505	0.251	0.461	0.532	0.431	0.641	0.251
75	0.479	0.211	0.433	0.509	0.408	0.623	0.211
76	0.442	0.154	0.392	0.490	0.382	0.595	0.154
77	0.512	0.260	0.468	0.523	0.430	0.646	0.260
78	0.480	0.213	0.434	0.504	0.404	0.623	0.213
79	0.144	0.000	0.069	0.281	0.094	0.381	0.000
80	0.314	0.000	0.254	0.368	0.250	0.504	0.000
81	0.314	0.000	0.254	0.368	0.250	0.504	0.000
82	0.484	0.218	0.438	0.502	0.401	0.626	0.218
83	0.441	0.153	0.391	0.468	0.370	0.595	0.153
84	0.485	0.219	0.439	0.495	0.403	0.620	0.208
85	0.497	0.238	0.452	0.511	0.414	0.635	0.238
86	0.489	0.226	0.443	0.504	0.405	0.629	0.226
87	0.314	0.000	0.254	0.393	0.250	0.504	0.000
88	0.494	0.233	0.448	0.513	0.424	0.632	0.233
89	0.485	0.220	0.440	0.502	0.410	0.627	0.220
90	0.499	0.241	0.454	0.521	0.464	0.636	0.241
91	0.471	0.199	0.424	0.499	0.396	0.616	0.199
92	0.496	0.237	0.451	0.510	0.420	0.634	0.237
93	0.246	0.000	0.179	0.338	0.179	0.454	0.000
94	0.419	0.120	0.367	0.462	0.346	0.579	0.120
95	0.497	0.236	0.455	0.450	0.350	0.631	0.222
96	0.507	0.252	0.465	0.465	0.368	0.646	0.252
97	0.504	0.247	0.453	0.464	0.367	0.624	0.212
98	0.468	0.194	0.421	0.450	0.350	0.615	0.194
99	0.314	0.000	0.254	0.293	0.164	0.504	0.000
100	0.331	0.000	0.272	0.313	0.188	0.516	0.000
101	0.379	0.058	0.324	0.382	0.268	0.550	0.058
102	0.496	0.237	0.451	0.497	0.406	0.634	0.237
103	0.501	0.244	0.456	0.501	0.410	0.637	0.244
104	0.483	0.217	0.437	0.485	0.390	0.625	0.217
AD	0.568	0.845	0.619	0.551	0.659	0.415	0.849
Equity	0.733	0.313	0.656	0.759	0.595	0.938	0.308
$NSR_{95,i}$	0.010	0.231	0.019	0.000	0.029	0.000	0.240

Table A3.5e: Tables of performance measures (adequacy) calculated

Pipe	25	26	26	26	29	30	31
Node	F1	F1	F2	F3	F1	F1	F1
1	0.350	0.250	0.167	0.188	0.400	0.450	0.600
2	0.350	0.250	0.167	0.188	0.400	0.450	0.600
3	0.365	0.250	0.167	0.188	0.400	0.450	0.600
4	0.259	0.144	0.046	0.070	0.318	0.374	0.544
5	0.399	0.307	0.230	0.249	0.445	0.492	0.630
6	0.339	0.236	0.149	0.170	0.391	0.441	0.593
7	0.350	0.250	0.167	0.188	0.400	0.450	0.600
8	0.305	0.175	0.083	0.106	0.340	0.395	0.560
9	0.133	0.000	0.000	0.000	0.200	0.267	0.467
10	0.325	0.221	0.135	0.156	0.377	0.429	0.585
11	0.235	0.118	0.020	0.044	0.294	0.353	0.529
12	0.000	0.000	0.000	0.000	0.025	0.106	0.350
13	0.362	0.263	0.180	0.200	0.412	0.460	0.607
14	0.444	0.352	0.278	0.296	0.483	0.526	0.655
15	0.403	0.295	0.211	0.231	0.440	0.485	0.625
16	0.353	0.250	0.152	0.174	0.389	0.437	0.603
17	0.364	0.264	0.172	0.193	0.400	0.464	0.609
18	0.242	0.123	0.013	0.038	0.277	0.362	0.535
19	0.394	0.300	0.216	0.236	0.433	0.489	0.628
20	0.437	0.349	0.271	0.290	0.468	0.525	0.673
21	0.414	0.323	0.245	0.264	0.453	0.505	0.645
22	0.443	0.355	0.270	0.290	0.453	0.532	0.658
23	0.380	0.284	0.203	0.223	0.429	0.476	0.619
24	0.427	0.332	0.258	0.276	0.466	0.510	0.644
25	0.150	0.018	0.000	0.000	0.218	0.282	0.477
26	0.376	0.280	0.199	0.219	0.425	0.473	0.616
27	0.323	0.219	0.132	0.154	0.375	0.427	0.583
28	0.322	0.217	0.130	0.152	0.374	0.426	0.583
29	0.383	0.288	0.209	0.229	0.431	0.478	0.621
30	0.394	0.301	0.223	0.243	0.441	0.488	0.627
31	0.400	0.307	0.229	0.249	0.447	0.493	0.631
32	0.383	0.288	0.208	0.228	0.430	0.478	0.620
33	0.386	0.292	0.213	0.233	0.433	0.481	0.622
34	0.319	0.214	0.127	0.149	0.371	0.424	0.581
35	0.387	0.293	0.214	0.234	0.434	0.481	0.623
36	0.298	0.190	0.100	0.123	0.352	0.406	0.568
37	0.164	0.036	0.000	0.000	0.229	0.293	0.486
38	0.253	0.138	0.042	0.066	0.310	0.368	0.540
39	0.285	0.175	0.083	0.106	0.340	0.395	0.560
40	0.362	0.263	0.180	0.200	0.412	0.460	0.607
41	0.328	0.224	0.138	0.159	0.379	0.431	0.586
42	0.268	0.155	0.058	0.082	0.326	0.382	0.550
43	0.405	0.313	0.235	0.255	0.451	0.496	0.634
44	0.378	0.281	0.197	0.218	0.414	0.462	0.609
45	0.422	0.322	0.244	0.263	0.459	0.503	0.639
46	0.442	0.349	0.274	0.292	0.481	0.523	0.653
47	0.353	0.224	0.124	0.147	0.388	0.415	0.574
48	0.379	0.263	0.171	0.193	0.417	0.448	0.598
49	0.422	0.333	0.255	0.274	0.462	0.512	0.645
50	0.397	0.302	0.215	0.235	0.434	0.479	0.629
51	0.382	0.285	0.198	0.219	0.420	0.478	0.620

52	0.331	0.225	0.127	0.149	0.367	0.436	0.589
53	0.242	0.158	0.047	0.072	0.308	0.362	0.554
54	0.361	0.261	0.171	0.192	0.400	0.461	0.607
55	0.435	0.369	0.289	0.308	0.462	0.532	0.672
56	0.000	0.000	0.000	0.000	0.000	0.070	0.370
57	0.362	0.262	0.171	0.192	0.400	0.462	0.608
58	0.396	0.314	0.232	0.252	0.445	0.490	0.635
59	0.413	0.322	0.242	0.261	0.452	0.504	0.639
60	0.397	0.315	0.234	0.253	0.446	0.500	0.636
61	0.267	0.150	0.037	0.063	0.300	0.383	0.571
62	0.387	0.290	0.203	0.224	0.423	0.483	0.633
63	0.432	0.344	0.265	0.284	0.471	0.521	0.651
64	0.313	0.205	0.108	0.131	0.350	0.420	0.578
65	0.317	0.230	0.135	0.158	0.374	0.439	0.602
66	0.382	0.286	0.203	0.223	0.432	0.478	0.627
67	0.423	0.333	0.253	0.272	0.460	0.504	0.639
68	0.414	0.323	0.241	0.261	0.451	0.496	0.633
69	0.457	0.333	0.252	0.271	0.461	0.504	0.639
70	0.400	0.306	0.222	0.242	0.438	0.494	0.631
71	0.414	0.323	0.241	0.261	0.451	0.496	0.633
72	0.380	0.283	0.191	0.212	0.400	0.463	0.609
73	0.425	0.355	0.261	0.281	0.420	0.518	0.623
74	0.438	0.359	0.283	0.301	0.476	0.525	0.659
75	0.418	0.327	0.245	0.264	0.446	0.509	0.649
76	0.382	0.285	0.198	0.219	0.420	0.478	0.628
77	0.435	0.352	0.278	0.296	0.475	0.526	0.653
78	0.404	0.312	0.232	0.251	0.452	0.497	0.639
79	0.194	0.006	0.000	0.000	0.175	0.281	0.475
80	0.279	0.164	0.056	0.080	0.314	0.368	0.539
81	0.279	0.164	0.056	0.080	0.314	0.368	0.539
82	0.421	0.330	0.251	0.270	0.459	0.502	0.638
83	0.398	0.288	0.200	0.221	0.421	0.468	0.613
84	0.423	0.321	0.242	0.261	0.460	0.504	0.639
85	0.429	0.332	0.255	0.274	0.475	0.511	0.644
86	0.413	0.322	0.243	0.263	0.460	0.504	0.639
87	0.279	0.164	0.056	0.080	0.314	0.393	0.557
88	0.417	0.326	0.249	0.268	0.463	0.507	0.650
89	0.402	0.319	0.238	0.258	0.450	0.502	0.643
90	0.425	0.335	0.258	0.277	0.463	0.514	0.656
91	0.406	0.314	0.232	0.252	0.445	0.490	0.635
93	0.179	0.088	0.000	0.000	0.250	0.338	0.517
94	0.362	0.262	0.171	0.192	0.400	0.448	0.608
95	0.350	0.250	0.167	0.188	0.400	0.450	0.600
96	0.368	0.271	0.190	0.210	0.417	0.465	0.611
97	0.367	0.270	0.189	0.209	0.416	0.464	0.611
98	0.350	0.250	0.167	0.188	0.400	0.450	0.600
99	0.164	0.036	0.000	0.000	0.229	0.293	0.486
100	0.213	0.063	0.000	0.000	0.250	0.313	0.500
101	0.268	0.155	0.058	0.082	0.326	0.382	0.550
102	0.406	0.314	0.237	0.256	0.452	0.497	0.634
103	0.410	0.319	0.244	0.263	0.456	0.501	0.637
104	0.390	0.296	0.217	0.237	0.438	0.485	0.625
AD	0.649	0.748	0.829	0.810	0.607	0.553	0.401
Equity	0.610	0.460	0.338	0.367	0.674	0.756	0.942
$NSR_{95,1}$	0.019	0.087	0.221	0.192	0.019	0.010	0.000

Table A3.5f: Tables of performance measures (adequacy) calculated

Pipe	32	32	33	33	35		
Node	F1	F2	F1	F2	F1		
1	0.650	0.188	0.268	0.167	0.150		
2	0.650	0.188	0.268	0.167	0.150		
3	0.650	0.188	0.268	0.167	0.150		
4	0.600	0.070	0.164	0.046	0.028		
5	0.676	0.249	0.323	0.230	0.214		
6	0.643	0.170	0.254	0.149	0.133		
7	0.650	0.188	0.268	0.167	0.150		
8	0.615	0.106	0.195	0.083	0.065		
9	0.533	0.000	0.024	0.000	0.000		
10	0.637	0.156	0.240	0.135	0.117		
11	0.588	0.044	0.139	0.020	0.000		
12	0.431	0.000	0.000	0.000	0.000		
13	0.656	0.200	0.280	0.180	0.164		
14	0.697	0.296	0.367	0.278	0.264		
15	0.670	0.231	0.310	0.211	0.198		
16	0.658	0.197	0.285	0.175	0.167		
17	0.664	0.213	0.297	0.192	0.181		
18	0.604	0.072	0.140	0.013	0.000		
19	0.678	0.248	0.315	0.216	0.203		
20	0.714	0.331	0.387	0.297	0.286		
21	0.688	0.273	0.347	0.254	0.241		
22	0.703	0.304	0.380	0.285	0.278		
23	0.666	0.223	0.301	0.203	0.188		
24	0.688	0.276	0.348	0.258	0.243		
25	0.541	0.000	0.040	0.000	0.000		
26	0.664	0.219	0.297	0.199	0.183		
27	0.635	0.154	0.238	0.132	0.115		
28	0.635	0.152	0.236	0.130	0.113		
29	0.668	0.229	0.306	0.209	0.194		
30	0.674	0.243	0.318	0.223	0.208		
31	0.677	0.249	0.324	0.229	0.214		
32	0.668	0.228	0.305	0.208	0.193		
33	0.669	0.233	0.309	0.213	0.197		
34	0.633	0.149	0.233	0.127	0.110		
35	0.670	0.234	0.310	0.214	0.199		
36	0.622	0.123	0.210	0.100	0.082		
37	0.550	0.000	0.059	0.000	0.000		
38	0.598	0.066	0.158	0.042	0.023		
39	0.615	0.106	0.195	0.083	0.065		
40	0.656	0.200	0.280	0.180	0.164		
41	0.638	0.159	0.243	0.138	0.121		
42	0.605	0.082	0.175	0.058	0.041		
43	0.679	0.255	0.329	0.235	0.221		
44	0.657	0.203	0.283	0.182	0.166		
45	0.683	0.263	0.337	0.244	0.230		
46	0.696	0.292	0.363	0.274	0.260		
47	0.635	0.147	0.237	0.124	0.113		
48	0.654	0.193	0.277	0.171	0.159		
49	0.688	0.274	0.347	0.255	0.242		
50	0.679	0.250	0.329	0.230	0.220		
51	0.665	0.219	0.300	0.198	0.185		

52	0.647	0.174	0.262	0.151	0.141		
53	0.619	0.106	0.172	0.047	0.036		
54	0.661	0.208	0.291	0.187	0.175		
55	0.709	0.319	0.391	0.301	0.292		
56	0.550	0.000	0.000	0.000	0.000		
57	0.662	0.209	0.276	0.171	0.158		
58	0.679	0.252	0.328	0.232	0.219		
59	0.687	0.270	0.345	0.251	0.239		
60	0.685	0.264	0.341	0.245	0.233		
61	0.650	0.172	0.268	0.148	0.146		
62	0.690	0.274	0.353	0.254	0.246		
63	0.705	0.311	0.384	0.293	0.283		
64	0.638	0.153	0.242	0.131	0.118		
65	0.665	0.215	0.245	0.135	0.122		
66	0.677	0.247	0.313	0.215	0.202		
67	0.688	0.272	0.347	0.253	0.240		
68	0.677	0.248	0.325	0.229	0.215		
69	0.688	0.271	0.347	0.252	0.240		
70	0.675	0.242	0.320	0.222	0.210		
71	0.683	0.261	0.337	0.241	0.229		
72	0.654	0.193	0.277	0.171	0.159		
73	0.685	0.259	0.341	0.239	0.232		
74	0.711	0.325	0.396	0.307	0.297		
75	0.700	0.298	0.373	0.279	0.270		
76	0.678	0.248	0.313	0.213	0.201		
77	0.698	0.297	0.368	0.279	0.266		
78	0.683	0.261	0.336	0.242	0.229		
79	0.531	0.000	0.020	0.000	0.000		
80	0.607	0.080	0.179	0.056	0.044		
81	0.607	0.080	0.179	0.056	0.044		
82	0.687	0.270	0.345	0.251	0.238		
83	0.666	0.221	0.302	0.200	0.188		
84	0.683	0.261	0.336	0.242	0.228		
85	0.688	0.274	0.347	0.255	0.241		
86	0.683	0.263	0.337	0.243	0.230		
87	0.607	0.080	0.179	0.056	0.044		
89	0.694	0.285	0.334	0.238	0.225		
90	0.709	0.320	0.358	0.267	0.254		
91	0.679	0.252	0.328	0.232	0.219		
92	0.691	0.280	0.346	0.253	0.240		
93	0.588	0.031	0.103	0.000	0.000		
94	0.662	0.209	0.276	0.171	0.158		
95	0.650	0.188	0.268	0.167	0.150		
96	0.660	0.210	0.289	0.190	0.174		
97	0.659	0.209	0.287	0.189	0.172		
98	0.650	0.188	0.268	0.167	0.150		
99	0.550	0.000	0.059	0.000	0.000		
100	0.575	0.012	0.111	0.000	0.000		
101	0.605	0.082	0.175	0.058	0.041		
102	0.680	0.256	0.330	0.237	0.222		
103	0.682	0.263	0.336	0.244	0.229		
104	0.671	0.237	0.313	0.217	0.202		
AD	0.347	0.803	0.728	0.825	0.837		
Equity	0.913	0.378	0.491	0.345	0.326		
NSR$_{95,1}$	0.000	0.173	0.067	0.212	0.212		

Table A3.6a: Tables of performance measures (severity) calculated

Pipe	1	1	1	4	4	5	7
Node	**F2**	**F3**	**F4**	**F2**	**F3**	**F1**	**F1**
1	0.236	0.206	0.217	0.142	0.109	0.192	0.156
2	0.317	0.277	0.291	0.198	0.153	0.259	0.200
3	0.254	0.222	0.234	0.161	0.125	0.208	0.157
4	0.348	0.304	0.320	0.230	0.178	0.266	0.219
5	0.302	0.264	0.277	0.184	0.142	0.247	0.189
6	0.297	0.260	0.273	0.189	0.147	0.237	0.157
7	0.413	0.361	0.379	0.260	0.202	0.331	0.240
8	0.278	0.243	0.256	0.187	0.145	0.227	0.161
9	0.330	0.292	0.307	0.249	0.194	0.273	0.194
10	0.343	0.300	0.315	0.227	0.176	0.281	0.218
11	0.305	0.267	0.281	0.214	0.166	0.249	0.194
12	0.443	0.443	0.443	0.443	0.364	0.443	0.360
13	0.255	0.223	0.235	0.162	0.125	0.205	0.156
14	0.227	0.198	0.208	0.134	0.103	0.185	0.142
15	0.254	0.223	0.234	0.162	0.126	0.208	0.158
16	0.293	0.256	0.269	0.196	0.152	0.233	0.175
17	0.277	0.242	0.254	0.187	0.146	0.221	0.171
18	0.330	0.297	0.312	0.251	0.196	0.268	0.200
19	0.255	0.223	0.235	0.164	0.127	0.206	0.159
20	0.237	0.208	0.218	0.144	0.112	0.192	0.147
21	0.241	0.211	0.221	0.149	0.115	0.197	0.151
22	0.254	0.223	0.234	0.162	0.126	0.204	0.155
23	0.240	0.210	0.220	0.145	0.112	0.189	0.154
24	0.288	0.252	0.265	0.166	0.128	0.226	0.183
25	0.420	0.379	0.399	0.315	0.245	0.341	0.251
26	0.243	0.213	0.223	0.150	0.116	0.199	0.151
27	0.355	0.311	0.326	0.230	0.178	0.290	0.208
28	0.264	0.231	0.243	0.173	0.134	0.221	0.168
29	0.308	0.270	0.284	0.192	0.148	0.252	0.196
30	0.242	0.212	0.222	0.148	0.115	0.195	0.147
31	0.322	0.282	0.296	0.197	0.152	0.263	0.196
32	0.243	0.213	0.223	0.150	0.116	0.199	0.149
33	0.245	0.214	0.225	0.149	0.115	0.197	0.144
34	0.393	0.344	0.362	0.264	0.205	0.321	0.227
35	0.311	0.272	0.286	0.191	0.147	0.250	0.183
36	0.280	0.245	0.257	0.185	0.144	0.229	0.178
37	0.330	0.292	0.307	0.242	0.188	0.273	0.212
38	0.298	0.261	0.274	0.207	0.161	0.244	0.190
39	0.285	0.249	0.262	0.194	0.151	0.233	0.182
40	0.325	0.284	0.299	0.206	0.160	0.265	0.194
41	0.268	0.235	0.247	0.173	0.134	0.219	0.171
42	0.293	0.256	0.269	0.204	0.159	0.240	0.185
43	0.292	0.256	0.269	0.176	0.136	0.236	0.183
44	0.342	0.299	0.314	0.220	0.170	0.280	0.212
45	0.303	0.265	0.279	0.184	0.142	0.248	0.190
46	0.228	0.199	0.210	0.137	0.106	0.186	0.143
47	0.288	0.252	0.265	0.205	0.159	0.236	0.176
48	0.275	0.241	0.253	0.182	0.142	0.220	0.166
49	0.239	0.209	0.220	0.145	0.112	0.193	0.150
50	0.391	0.342	0.360	0.249	0.193	0.314	0.238
51	0.263	0.230	0.242	0.171	0.133	0.211	0.164

52	0.295	0.258	0.271	0.201	0.156	0.234	0.181
53	0.328	0.287	0.302	0.240	0.187	0.268	0.200
54	0.273	0.239	0.251	0.179	0.139	0.219	0.169
55	0.242	0.212	0.223	0.151	0.116	0.198	0.151
56	0.330	0.330	0.330	0.330	0.330	0.330	0.301
57	0.274	0.240	0.252	0.183	0.142	0.219	0.170
58	0.249	0.218	0.229	0.157	0.121	0.204	0.156
59	0.313	0.274	0.288	0.195	0.151	0.253	0.196
60	0.317	0.277	0.291	0.201	0.155	0.259	0.198
61	0.330	0.292	0.307	0.249	0.194	0.273	0.203
62	0.264	0.231	0.243	0.173	0.134	0.216	0.163
63	0.323	0.282	0.297	0.196	0.152	0.261	0.199
64	0.291	0.255	0.268	0.200	0.155	0.238	0.180
65	0.287	0.251	0.264	0.196	0.153	0.230	0.178
66	0.255	0.223	0.235	0.163	0.126	0.206	0.159
67	0.331	0.290	0.304	0.205	0.158	0.271	0.207
68	0.248	0.217	0.228	0.157	0.122	0.203	0.154
69	0.248	0.217	0.228	0.156	0.121	0.200	0.152
70	0.255	0.223	0.234	0.164	0.127	0.205	0.158
71	0.248	0.217	0.228	0.157	0.122	0.203	0.154
72	0.276	0.241	0.253	0.185	0.144	0.220	0.166
73	0.278	0.243	0.256	0.187	0.145	0.221	0.166
74	0.233	0.204	0.214	0.141	0.109	0.191	0.146
75	0.249	0.218	0.229	0.154	0.119	0.201	0.153
76	0.263	0.230	0.242	0.171	0.133	0.211	0.164
77	0.232	0.203	0.214	0.138	0.106	0.188	0.144
78	0.245	0.214	0.225	0.153	0.118	0.200	0.153
79	0.330	0.330	0.330	0.309	0.242	0.315	0.229
80	0.323	0.283	0.297	0.231	0.180	0.264	0.197
81	0.323	0.283	0.297	0.231	0.180	0.264	0.197
82	0.243	0.213	0.224	0.153	0.118	0.199	0.152
83	0.263	0.231	0.242	0.169	0.131	0.211	0.160
84	0.243	0.213	0.223	0.150	0.116	0.199	0.151
85	0.237	0.208	0.218	0.144	0.112	0.192	0.147
86	0.241	0.211	0.221	0.148	0.115	0.197	0.151
87	0.323	0.283	0.297	0.231	0.180	0.264	0.197
88	0.354	0.310	0.326	0.216	0.167	0.287	0.222
89	0.301	0.264	0.277	0.186	0.144	0.243	0.189
90	0.236	0.207	0.217	0.145	0.112	0.193	0.148
91	0.249	0.218	0.229	0.157	0.121	0.201	0.156
92	0.238	0.208	0.218	0.147	0.114	0.194	0.149
93	0.330	0.311	0.327	0.272	0.212	0.281	0.216
94	0.274	0.240	0.252	0.183	0.142	0.219	0.170
95	0.259	0.227	0.238	0.169	0.131	0.212	0.165
96	0.252	0.220	0.232	0.160	0.124	0.206	0.160
97	0.252	0.221	0.232	0.162	0.126	0.207	0.161
98	0.354	0.309	0.325	0.229	0.177	0.289	0.225
99	0.420	0.371	0.390	0.307	0.240	0.347	0.270
100	0.315	0.276	0.290	0.227	0.177	0.258	0.200
101	0.300	0.263	0.276	0.204	0.159	0.246	0.185
102	0.302	0.265	0.278	0.183	0.142	0.244	0.187
103	0.365	0.320	0.336	0.218	0.168	0.295	0.229
104	0.306	0.268	0.281	0.189	0.147	0.250	0.191

Table A3.6b: Tables of performance measures (severity) calculated

Pipe	9	9	10	11	11	12	13
Node	**F1**	**F2**	**F2**	**F1**	**F2**	**F1**	**F1**
1	0.141	0.181	0.275	0.275	0.275	0.281	0.220
2	0.180	0.231	0.343	0.350	0.350	0.357	0.280
3	0.141	0.182	0.270	0.275	0.275	0.275	0.215
4	0.204	0.263	0.401	0.412	0.412	0.409	0.320
5	0.166	0.213	0.320	0.323	0.323	0.330	0.259
6	0.152	0.196	0.315	0.322	0.322	0.321	0.251
7	0.216	0.278	0.429	0.437	0.437	0.446	0.350
8	0.130	0.168	0.244	0.059	0.059	0.301	0.236
9	0.165	0.213	0.306	0.330	0.330	0.330	0.282
10	0.191	0.245	0.363	0.363	0.363	0.334	0.265
11	0.170	0.218	0.323	0.323	0.323	0.321	0.244
12	0.315	0.405	0.443	0.443	0.443	0.443	0.443
13	0.137	0.177	0.271	0.275	0.275	0.276	0.216
14	0.125	0.161	0.243	0.245	0.245	0.247	0.194
15	0.139	0.179	0.275	0.275	0.275	0.281	0.216
16	0.158	0.204	0.311	0.318	0.318	0.317	0.241
17	0.150	0.193	0.293	0.300	0.300	0.299	0.234
18	0.182	0.235	0.330	0.330	0.330	0.330	0.278
19	0.140	0.180	0.271	0.275	0.275	0.276	0.216
20	0.130	0.168	0.251	0.254	0.254	0.256	0.199
21	0.134	0.172	0.258	0.258	0.258	0.263	0.204
22	0.139	0.179	0.270	0.275	0.275	0.276	0.216
23	0.136	0.175	0.263	0.267	0.267	0.268	0.210
24	0.160	0.206	0.309	0.312	0.312	0.318	0.249
25	0.231	0.298	0.420	0.420	0.420	0.420	0.367
26	0.135	0.173	0.264	0.268	0.268	0.270	0.211
27	0.193	0.248	0.377	0.385	0.385	0.392	0.308
28	0.147	0.189	0.287	0.287	0.287	0.293	0.230
29	0.172	0.221	0.332	0.332	0.332	0.339	0.265
30	0.125	0.161	0.230	0.253	0.253	0.258	0.202
31	0.170	0.219	0.312	0.325	0.325	0.348	0.273
32	0.127	0.163	0.232	0.147	0.147	0.263	0.206
33	0.120	0.155	0.227	0.124	0.124	0.261	0.204
34	0.178	0.230	0.345	0.083	0.083	0.426	0.333
35	0.152	0.197	0.287	0.158	0.158	0.331	0.259
36	0.156	0.200	0.297	0.297	0.297	0.297	0.227
37	0.185	0.239	0.330	0.330	0.330	0.330	0.265
38	0.166	0.214	0.316	0.316	0.316	0.315	0.240
39	0.159	0.204	0.303	0.303	0.303	0.286	0.197
40	0.168	0.217	0.339	0.350	0.350	0.352	0.275
41	0.149	0.192	0.284	0.284	0.284	0.285	0.219
42	0.163	0.210	0.311	0.318	0.318	0.301	0.228
43	0.161	0.207	0.310	0.313	0.313	0.319	0.247
44	0.186	0.240	0.363	0.369	0.369	0.377	0.289
45	0.166	0.214	0.322	0.326	0.326	0.333	0.257
46	0.126	0.162	0.244	0.246	0.246	0.249	0.195
47	0.155	0.200	0.315	0.323	0.323	0.321	0.251
48	0.149	0.192	0.292	0.298	0.298	0.298	0.233
49	0.132	0.169	0.253	0.256	0.256	0.259	0.203
50	0.213	0.274	0.415	0.422	0.422	0.423	0.325
51	0.144	0.185	0.279	0.284	0.284	0.285	0.223

52	0.159	0.205	0.313	0.321	0.321	0.319	0.249
53	0.176	0.227	0.330	0.330	0.330	0.330	0.278
54	0.149	0.191	0.289	0.295	0.295	0.295	0.231
55	0.133	0.171	0.257	0.261	0.261	0.262	0.206
56	0.284	0.330	0.330	0.330	0.330	0.330	0.330
57	0.149	0.192	0.290	0.296	0.296	0.296	0.232
58	0.137	0.176	0.264	0.268	0.268	0.270	0.211
59	0.172	0.221	0.332	0.336	0.336	0.339	0.265
60	0.173	0.223	0.336	0.341	0.341	0.343	0.269
61	0.179	0.230	0.330	0.330	0.330	0.330	0.282
62	0.144	0.185	0.285	0.285	0.285	0.285	0.223
63	0.177	0.228	0.342	0.346	0.346	0.349	0.270
64	0.158	0.203	0.316	0.316	0.316	0.322	0.247
65	0.156	0.201	0.305	0.311	0.311	0.311	0.238
66	0.140	0.180	0.271	0.275	0.275	0.277	0.216
67	0.181	0.234	0.356	0.356	0.356	0.363	0.281
68	0.136	0.175	0.267	0.267	0.267	0.273	0.210
69	0.136	0.175	0.263	0.267	0.267	0.269	0.210
70	0.139	0.179	0.270	0.275	0.275	0.276	0.216
71	0.136	0.175	0.267	0.267	0.267	0.273	0.210
72	0.150	0.193	0.292	0.299	0.299	0.298	0.234
73	0.150	0.194	0.295	0.303	0.303	0.301	0.236
74	0.128	0.165	0.250	0.250	0.250	0.255	0.198
75	0.136	0.176	0.264	0.268	0.268	0.270	0.208
76	0.144	0.185	0.279	0.284	0.284	0.285	0.223
77	0.128	0.165	0.246	0.248	0.248	0.251	0.195
78	0.135	0.173	0.260	0.263	0.263	0.265	0.208
79	0.214	0.276	0.330	0.330	0.330	0.330	0.330
80	0.174	0.224	0.330	0.330	0.330	0.330	0.274
81	0.174	0.224	0.330	0.330	0.330	0.330	0.274
82	0.133	0.172	0.262	0.262	0.262	0.267	0.206
83	0.144	0.185	0.280	0.285	0.285	0.285	0.223
84	0.133	0.171	0.261	0.261	0.261	0.266	0.206
85	0.130	0.168	0.251	0.254	0.254	0.256	0.201
86	0.132	0.170	0.258	0.258	0.258	0.264	0.204
87	0.174	0.224	0.330	0.330	0.330	0.330	0.274
88	0.195	0.251	0.376	0.380	0.380	0.383	0.300
89	0.166	0.213	0.320	0.324	0.324	0.326	0.252
90	0.131	0.169	0.253	0.253	0.253	0.258	0.200
91	0.137	0.176	0.264	0.268	0.268	0.270	0.211
92	0.132	0.170	0.255	0.255	0.255	0.260	0.201
93	0.191	0.246	0.330	0.330	0.330	0.330	0.301
94	0.149	0.192	0.290	0.296	0.296	0.296	0.232
95	0.144	0.185	0.275	0.275	0.275	0.276	0.212
96	0.140	0.181	0.267	0.267	0.267	0.273	0.207
97	0.141	0.181	0.268	0.268	0.268	0.269	0.208
98	0.197	0.253	0.375	0.375	0.375	0.376	0.289
99	0.236	0.304	0.420	0.420	0.420	0.420	0.337
100	0.175	0.226	0.330	0.330	0.330	0.330	0.259
101	0.163	0.210	0.318	0.318	0.318	0.301	0.235
102	0.166	0.214	0.320	0.324	0.324	0.327	0.256
103	0.201	0.258	0.387	0.392	0.392	0.399	0.313
104	0.168	0.215	0.329	0.333	0.333	0.336	0.263

Table A3.6c: Tables of performance measures (severity) calculated

Pipe	14	14	14	15	15	15	16
Node	F2	F1	F2	F1	F2	F3	F1
1	0.215	0.206	0.275	0.149	0.275	0.227	0.242
2	0.273	0.263	0.343	0.189	0.350	0.289	0.309
3	0.210	0.202	0.270	0.149	0.275	0.227	0.243
4	0.312	0.301	0.401	0.216	0.401	0.331	0.351
5	0.252	0.243	0.320	0.175	0.323	0.267	0.285
6	0.246	0.236	0.315	0.170	0.315	0.260	0.270
7	0.341	0.328	0.429	0.236	0.437	0.361	0.386
8	0.230	0.222	0.244	0.159	0.295	0.243	0.266
9	0.286	0.275	0.306	0.198	0.330	0.303	0.319
10	0.278	0.268	0.363	0.192	0.356	0.294	0.327
11	0.239	0.231	0.323	0.170	0.315	0.260	0.291
12	0.391	0.381	0.443	0.255	0.443	0.391	0.443
13	0.211	0.203	0.271	0.146	0.271	0.223	0.232
14	0.187	0.181	0.243	0.131	0.243	0.200	0.216
15	0.211	0.203	0.275	0.146	0.270	0.223	0.243
16	0.236	0.228	0.311	0.163	0.303	0.250	0.273
17	0.229	0.220	0.293	0.158	0.293	0.242	0.258
18	0.272	0.262	0.330	0.188	0.330	0.287	0.314
19	0.208	0.201	0.271	0.144	0.267	0.220	0.240
20	0.194	0.187	0.251	0.134	0.249	0.205	0.224
21	0.199	0.191	0.258	0.138	0.255	0.211	0.230
22	0.207	0.199	0.270	0.146	0.270	0.223	0.239
23	0.205	0.197	0.263	0.142	0.263	0.217	0.233
24	0.243	0.234	0.309	0.168	0.312	0.257	0.275
25	0.359	0.346	0.420	0.258	0.420	0.394	0.399
26	0.204	0.196	0.264	0.143	0.264	0.218	0.235
27	0.300	0.289	0.377	0.208	0.385	0.317	0.339
28	0.224	0.215	0.287	0.155	0.287	0.237	0.258
29	0.259	0.249	0.332	0.179	0.332	0.274	0.294
30	0.200	0.192	0.230	0.138	0.256	0.212	0.228
31	0.266	0.256	0.312	0.184	0.342	0.282	0.304
32	0.201	0.193	0.232	0.141	0.261	0.215	0.232
33	0.203	0.195	0.227	0.140	0.260	0.214	0.230
34	0.334	0.321	0.345	0.231	0.428	0.353	0.376
35	0.257	0.247	0.287	0.178	0.330	0.272	0.292
36	0.209	0.202	0.297	0.137	0.256	0.210	0.267
37	0.235	0.228	0.330	0.161	0.301	0.248	0.318
38	0.212	0.206	0.316	0.142	0.265	0.217	0.284
39	0.224	0.216	0.303	0.159	0.295	0.243	0.272
40	0.269	0.259	0.339	0.186	0.344	0.284	0.310
41	0.214	0.206	0.284	0.151	0.280	0.230	0.256
42	0.236	0.228	0.311	0.168	0.311	0.256	0.280
43	0.241	0.232	0.310	0.169	0.313	0.258	0.276
44	0.283	0.272	0.363	0.200	0.369	0.305	0.320
45	0.251	0.242	0.322	0.174	0.322	0.265	0.286
46	0.189	0.182	0.244	0.132	0.244	0.201	0.218
47	0.239	0.231	0.315	0.170	0.315	0.260	0.276
48	0.223	0.215	0.292	0.157	0.292	0.241	0.257
49	0.194	0.187	0.253	0.135	0.251	0.207	0.226
50	0.318	0.306	0.415	0.220	0.407	0.336	0.367
51	0.214	0.206	0.279	0.151	0.279	0.230	0.247

52	0.237	0.229	0.313	0.169	0.313	0.258	0.274
53	0.272	0.262	0.330	0.188	0.330	0.287	0.314
54	0.218	0.210	0.289	0.153	0.284	0.234	0.256
55	0.201	0.193	0.257	0.139	0.257	0.212	0.228
56	0.330	0.330	0.330	0.294	0.330	0.330	0.330
57	0.222	0.214	0.290	0.157	0.290	0.240	0.256
58	0.206	0.199	0.264	0.143	0.264	0.218	0.235
59	0.256	0.246	0.332	0.179	0.332	0.274	0.295
60	0.262	0.252	0.336	0.181	0.336	0.277	0.298
61	0.267	0.258	0.330	0.191	0.330	0.292	0.308
62	0.218	0.210	0.285	0.151	0.280	0.231	0.247
63	0.264	0.254	0.342	0.182	0.338	0.279	0.304
64	0.241	0.232	0.316	0.167	0.309	0.255	0.278
65	0.228	0.220	0.305	0.161	0.298	0.246	0.268
66	0.208	0.201	0.271	0.146	0.271	0.223	0.240
67	0.274	0.264	0.356	0.189	0.351	0.290	0.316
68	0.205	0.197	0.267	0.142	0.263	0.217	0.237
69	0.202	0.195	0.263	0.142	0.263	0.217	0.233
70	0.211	0.203	0.270	0.146	0.270	0.223	0.239
71	0.205	0.197	0.267	0.142	0.263	0.217	0.237
72	0.223	0.215	0.292	0.158	0.292	0.241	0.257
73	0.224	0.216	0.295	0.159	0.295	0.243	0.259
74	0.193	0.185	0.250	0.134	0.247	0.204	0.220
75	0.203	0.196	0.264	0.141	0.260	0.215	0.234
76	0.214	0.206	0.279	0.148	0.274	0.226	0.247
77	0.189	0.182	0.246	0.132	0.244	0.201	0.220
78	0.203	0.195	0.260	0.140	0.260	0.214	0.231
79	0.320	0.309	0.330	0.231	0.330	0.330	0.330
80	0.268	0.258	0.330	0.185	0.330	0.283	0.299
81	0.268	0.258	0.330	0.185	0.330	0.283	0.299
82	0.201	0.194	0.262	0.139	0.258	0.213	0.229
83	0.218	0.210	0.280	0.151	0.280	0.231	0.247
84	0.201	0.193	0.261	0.139	0.258	0.213	0.232
85	0.196	0.189	0.251	0.136	0.251	0.208	0.224
86	0.199	0.192	0.258	0.138	0.255	0.211	0.230
87	0.268	0.258	0.330	0.185	0.330	0.283	0.299
88	0.290	0.279	0.376	0.201	0.372	0.307	0.335
89	0.244	0.234	0.320	0.171	0.316	0.260	0.284
90	0.195	0.188	0.253	0.135	0.250	0.207	0.225
91	0.206	0.199	0.264	0.143	0.264	0.218	0.235
92	0.196	0.189	0.255	0.136	0.252	0.208	0.227
93	0.284	0.275	0.330	0.204	0.330	0.311	0.329
94	0.222	0.214	0.290	0.157	0.290	0.240	0.256
95	0.189	0.184	0.275	0.128	0.238	0.196	0.248
96	0.192	0.186	0.267	0.131	0.243	0.200	0.241
97	0.194	0.187	0.268	0.134	0.248	0.205	0.241
98	0.278	0.269	0.375	0.196	0.363	0.299	0.338
99	0.330	0.319	0.420	0.236	0.420	0.360	0.405
100	0.254	0.245	0.330	0.181	0.330	0.276	0.301
101	0.242	0.233	0.318	0.168	0.311	0.256	0.280
102	0.250	0.241	0.320	0.173	0.320	0.265	0.286
103	0.306	0.294	0.387	0.211	0.392	0.323	0.345
104	0.257	0.247	0.329	0.178	0.329	0.271	0.292

Table A3.6d: Tables of performance measures (severity) calculated

Pipe	17	17	18	19	20	21	21
Node	**F1**	**F2**	**F1**	**F1**	**F1**	**F1**	**F2**
1	0.182	0.275	0.198	0.182	0.215	0.132	0.275
2	0.231	0.350	0.252	0.231	0.273	0.168	0.350
3	0.182	0.275	0.198	0.182	0.215	0.132	0.275
4	0.264	0.401	0.288	0.263	0.311	0.192	0.401
5	0.213	0.323	0.233	0.213	0.252	0.155	0.323
6	0.208	0.315	0.226	0.207	0.245	0.155	0.322
7	0.289	0.437	0.315	0.289	0.341	0.210	0.437
8	0.195	0.295	0.212	0.200	0.236	0.141	0.295
9	0.242	0.330	0.264	0.242	0.286	0.176	0.330
10	0.235	0.356	0.262	0.240	0.284	0.174	0.363
11	0.208	0.315	0.226	0.214	0.252	0.155	0.323
12	0.330	0.443	0.374	0.396	0.443	0.260	0.443
13	0.179	0.271	0.195	0.178	0.211	0.130	0.271
14	0.160	0.243	0.174	0.156	0.185	0.116	0.243
15	0.178	0.270	0.194	0.170	0.206	0.129	0.270
16	0.200	0.303	0.217	0.180	0.220	0.144	0.303
17	0.193	0.293	0.211	0.177	0.216	0.140	0.293
18	0.230	0.330	0.250	0.211	0.260	0.166	0.330
19	0.176	0.267	0.195	0.169	0.204	0.130	0.271
20	0.164	0.249	0.179	0.150	0.186	0.119	0.249
21	0.168	0.255	0.183	0.163	0.193	0.122	0.255
22	0.178	0.270	0.194	0.154	0.197	0.129	0.270
23	0.174	0.263	0.189	0.173	0.205	0.128	0.267
24	0.206	0.312	0.224	0.206	0.243	0.150	0.312
25	0.315	0.420	0.344	0.302	0.372	0.229	0.420
26	0.175	0.264	0.190	0.174	0.206	0.127	0.264
27	0.254	0.385	0.277	0.254	0.300	0.185	0.385
28	0.189	0.287	0.207	0.189	0.224	0.138	0.287
29	0.219	0.332	0.239	0.219	0.259	0.159	0.332
30	0.169	0.256	0.184	0.169	0.200	0.123	0.256
31	0.226	0.342	0.246	0.225	0.266	0.164	0.342
32	0.172	0.261	0.188	0.172	0.204	0.125	0.261
33	0.171	0.260	0.187	0.171	0.203	0.125	0.260
34	0.282	0.428	0.308	0.282	0.334	0.205	0.428
35	0.218	0.330	0.238	0.218	0.257	0.158	0.330
36	0.180	0.274	0.195	0.196	0.232	0.136	0.285
37	0.205	0.312	0.230	0.233	0.276	0.158	0.330
38	0.184	0.280	0.199	0.209	0.247	0.139	0.294
39	0.195	0.295	0.212	0.200	0.236	0.145	0.303
40	0.227	0.344	0.248	0.227	0.273	0.168	0.350
41	0.184	0.280	0.201	0.188	0.222	0.134	0.280
42	0.205	0.311	0.223	0.204	0.242	0.149	0.311
43	0.207	0.313	0.225	0.204	0.241	0.150	0.313
44	0.244	0.369	0.266	0.239	0.282	0.177	0.369
45	0.213	0.322	0.231	0.209	0.247	0.154	0.322
46	0.161	0.244	0.176	0.157	0.186	0.117	0.244
47	0.208	0.315	0.226	0.193	0.229	0.150	0.315
48	0.192	0.292	0.210	0.182	0.216	0.140	0.292
49	0.166	0.251	0.181	0.161	0.193	0.121	0.253
50	0.269	0.407	0.293	0.249	0.302	0.195	0.407
51	0.184	0.279	0.201	0.172	0.209	0.134	0.279

52	0.206	0.313	0.225	0.186	0.228	0.149	0.313
53	0.230	0.330	0.250	0.202	0.250	0.166	0.330
54	0.187	0.284	0.204	0.178	0.216	0.139	0.289
55	0.170	0.257	0.185	0.149	0.190	0.123	0.257
56	0.330	0.330	0.330	0.284	0.330	0.257	0.330
57	0.192	0.290	0.209	0.178	0.216	0.139	0.290
58	0.175	0.264	0.190	0.165	0.199	0.127	0.264
59	0.219	0.332	0.239	0.209	0.252	0.159	0.332
60	0.222	0.336	0.242	0.210	0.253	0.161	0.336
61	0.234	0.330	0.254	0.194	0.253	0.169	0.330
62	0.185	0.280	0.201	0.166	0.208	0.134	0.280
63	0.223	0.338	0.243	0.212	0.255	0.164	0.342
64	0.204	0.309	0.222	0.191	0.227	0.148	0.309
65	0.197	0.298	0.214	0.185	0.219	0.142	0.298
66	0.179	0.271	0.195	0.169	0.200	0.130	0.271
67	0.232	0.351	0.252	0.223	0.269	0.168	0.351
68	0.174	0.263	0.189	0.166	0.201	0.126	0.263
69	0.174	0.263	0.189	0.164	0.198	0.126	0.263
70	0.179	0.270	0.194	0.167	0.202	0.129	0.270
71	0.174	0.263	0.189	0.166	0.201	0.126	0.263
72	0.193	0.292	0.210	0.177	0.216	0.140	0.292
73	0.195	0.295	0.212	0.171	0.216	0.141	0.295
74	0.163	0.247	0.178	0.154	0.188	0.118	0.247
75	0.172	0.260	0.187	0.162	0.195	0.124	0.260
76	0.184	0.279	0.201	0.168	0.204	0.134	0.279
77	0.161	0.244	0.176	0.157	0.188	0.117	0.244
78	0.172	0.260	0.187	0.164	0.197	0.124	0.260
79	0.282	0.330	0.307	0.237	0.299	0.204	0.330
80	0.226	0.330	0.246	0.209	0.248	0.164	0.330
81	0.226	0.330	0.246	0.209	0.248	0.164	0.330
82	0.170	0.258	0.185	0.164	0.198	0.123	0.258
83	0.184	0.280	0.201	0.176	0.208	0.134	0.280
84	0.170	0.258	0.185	0.167	0.197	0.125	0.261
85	0.166	0.251	0.181	0.161	0.193	0.120	0.251
86	0.169	0.255	0.184	0.164	0.196	0.122	0.255
87	0.226	0.330	0.246	0.200	0.248	0.164	0.330
88	0.248	0.376	0.270	0.239	0.282	0.180	0.376
89	0.209	0.316	0.227	0.202	0.239	0.151	0.316
90	0.165	0.250	0.180	0.158	0.177	0.120	0.250
91	0.175	0.264	0.190	0.165	0.199	0.127	0.264
92	0.166	0.252	0.181	0.162	0.191	0.121	0.252
93	0.249	0.330	0.271	0.218	0.271	0.180	0.330
94	0.192	0.290	0.209	0.178	0.216	0.139	0.290
95	0.166	0.252	0.180	0.182	0.215	0.122	0.257
96	0.163	0.247	0.177	0.177	0.209	0.117	0.247
97	0.164	0.248	0.181	0.177	0.209	0.124	0.260
98	0.239	0.363	0.261	0.248	0.293	0.173	0.363
99	0.288	0.420	0.313	0.297	0.351	0.208	0.420
100	0.221	0.330	0.240	0.227	0.268	0.160	0.330
101	0.205	0.311	0.223	0.204	0.242	0.149	0.311
102	0.212	0.320	0.231	0.211	0.249	0.154	0.320
103	0.258	0.392	0.282	0.258	0.306	0.188	0.392
104	0.217	0.329	0.236	0.216	0.256	0.158	0.329

Table A3.6e: Tables of performance measures (severity) calculated

Pipe	25	26	26	26	29	30	31
Node	F1	F1	F2	F3	F1	F1	F1
1	0.215	0.248	0.275	0.268	0.198	0.182	0.132
2	0.273	0.315	0.350	0.341	0.252	0.231	0.168
3	0.210	0.248	0.275	0.268	0.198	0.182	0.132
4	0.311	0.360	0.401	0.391	0.286	0.263	0.192
5	0.252	0.291	0.323	0.315	0.233	0.213	0.155
6	0.245	0.283	0.315	0.307	0.225	0.207	0.151
7	0.341	0.394	0.437	0.426	0.315	0.289	0.210
8	0.229	0.272	0.303	0.295	0.218	0.200	0.145
9	0.286	0.330	0.330	0.330	0.264	0.242	0.176
10	0.284	0.327	0.363	0.354	0.262	0.240	0.174
11	0.252	0.291	0.323	0.315	0.233	0.214	0.155
12	0.443	0.443	0.443	0.443	0.432	0.396	0.288
13	0.211	0.243	0.271	0.264	0.194	0.178	0.130
14	0.183	0.214	0.238	0.232	0.171	0.156	0.114
15	0.197	0.233	0.260	0.254	0.185	0.170	0.124
16	0.214	0.248	0.280	0.273	0.202	0.186	0.131
17	0.210	0.243	0.273	0.266	0.198	0.177	0.129
18	0.250	0.289	0.326	0.317	0.239	0.211	0.153
19	0.200	0.231	0.259	0.252	0.187	0.169	0.123
20	0.186	0.215	0.241	0.234	0.176	0.157	0.108
21	0.193	0.223	0.249	0.243	0.181	0.163	0.117
22	0.184	0.213	0.241	0.234	0.181	0.154	0.113
23	0.205	0.236	0.263	0.256	0.188	0.173	0.126
24	0.241	0.281	0.312	0.304	0.224	0.206	0.150
25	0.357	0.412	0.420	0.420	0.328	0.302	0.220
26	0.206	0.238	0.264	0.258	0.190	0.174	0.127
27	0.300	0.346	0.385	0.375	0.277	0.254	0.185
28	0.224	0.258	0.287	0.280	0.207	0.189	0.138
29	0.259	0.299	0.332	0.324	0.239	0.219	0.159
30	0.200	0.231	0.256	0.250	0.184	0.169	0.123
31	0.266	0.307	0.342	0.333	0.245	0.225	0.164
32	0.204	0.235	0.261	0.255	0.188	0.172	0.125
33	0.203	0.234	0.260	0.253	0.187	0.171	0.125
34	0.334	0.385	0.428	0.417	0.308	0.282	0.205
35	0.257	0.297	0.330	0.322	0.238	0.218	0.158
36	0.232	0.267	0.297	0.289	0.214	0.196	0.143
37	0.276	0.318	0.330	0.330	0.254	0.233	0.170
38	0.247	0.284	0.316	0.308	0.228	0.209	0.152
39	0.236	0.272	0.303	0.295	0.218	0.200	0.145
40	0.268	0.310	0.344	0.336	0.247	0.227	0.165
41	0.222	0.256	0.284	0.278	0.205	0.188	0.137
42	0.242	0.279	0.311	0.303	0.222	0.204	0.149
43	0.241	0.278	0.310	0.302	0.222	0.204	0.148
44	0.276	0.319	0.356	0.347	0.260	0.239	0.173
45	0.243	0.285	0.318	0.310	0.227	0.209	0.152
46	0.184	0.215	0.240	0.234	0.171	0.157	0.115
47	0.214	0.256	0.289	0.281	0.202	0.193	0.141
48	0.205	0.243	0.274	0.266	0.192	0.182	0.133
49	0.191	0.220	0.246	0.240	0.178	0.161	0.117
50	0.295	0.342	0.385	0.375	0.277	0.255	0.182
51	0.204	0.236	0.265	0.258	0.191	0.172	0.125

52	0.221	0.256	0.288	0.281	0.209	0.186	0.136
53	0.250	0.278	0.314	0.306	0.228	0.211	0.147
54	0.211	0.244	0.274	0.267	0.198	0.178	0.130
55	0.186	0.208	0.235	0.228	0.178	0.154	0.108
56	0.330	0.330	0.330	0.330	0.330	0.307	0.208
57	0.211	0.244	0.274	0.267	0.198	0.178	0.129
58	0.199	0.226	0.253	0.247	0.183	0.168	0.120
59	0.248	0.286	0.320	0.312	0.231	0.209	0.152
60	0.253	0.288	0.322	0.314	0.233	0.210	0.153
61	0.242	0.281	0.318	0.309	0.231	0.204	0.142
62	0.202	0.234	0.263	0.256	0.190	0.171	0.121
63	0.252	0.291	0.326	0.317	0.235	0.212	0.155
64	0.227	0.262	0.294	0.287	0.215	0.191	0.139
65	0.225	0.254	0.285	0.278	0.207	0.185	0.131
66	0.204	0.236	0.263	0.256	0.187	0.172	0.123
67	0.260	0.300	0.336	0.328	0.243	0.223	0.162
68	0.193	0.223	0.250	0.244	0.181	0.166	0.121
69	0.179	0.220	0.247	0.241	0.178	0.164	0.119
70	0.198	0.229	0.257	0.250	0.185	0.167	0.122
71	0.193	0.223	0.250	0.244	0.181	0.166	0.121
72	0.205	0.237	0.267	0.260	0.198	0.177	0.129
73	0.190	0.213	0.244	0.237	0.191	0.159	0.124
74	0.185	0.212	0.237	0.231	0.173	0.157	0.113
75	0.192	0.222	0.249	0.243	0.183	0.162	0.116
76	0.204	0.236	0.265	0.258	0.191	0.172	0.123
77	0.186	0.214	0.238	0.232	0.173	0.156	0.115
78	0.197	0.227	0.253	0.247	0.181	0.166	0.119
79	0.266	0.328	0.330	0.330	0.272	0.237	0.173
80	0.238	0.276	0.312	0.304	0.226	0.209	0.152
81	0.238	0.276	0.312	0.304	0.226	0.209	0.152
82	0.191	0.221	0.247	0.241	0.179	0.164	0.119
83	0.199	0.235	0.264	0.257	0.191	0.176	0.128
84	0.190	0.224	0.250	0.244	0.178	0.164	0.119
85	0.188	0.220	0.246	0.240	0.173	0.161	0.117
86	0.194	0.224	0.250	0.243	0.178	0.164	0.119
87	0.238	0.276	0.312	0.304	0.226	0.200	0.146
88	0.286	0.330	0.368	0.359	0.263	0.242	0.172
89	0.242	0.276	0.309	0.301	0.223	0.202	0.145
90	0.190	0.219	0.245	0.239	0.177	0.160	0.114
91	0.196	0.226	0.253	0.247	0.183	0.168	0.120
92	0.191	0.221	0.247	0.240	0.179	0.162	0.117
93	0.271	0.301	0.330	0.330	0.248	0.218	0.159
94	0.211	0.244	0.274	0.267	0.198	0.182	0.129
95	0.215	0.248	0.275	0.268	0.198	0.182	0.132
96	0.209	0.241	0.267	0.261	0.192	0.177	0.128
97	0.209	0.241	0.268	0.261	0.193	0.177	0.128
98	0.293	0.338	0.375	0.365	0.270	0.248	0.180
99	0.351	0.405	0.420	0.420	0.324	0.297	0.216
100	0.260	0.309	0.330	0.330	0.248	0.227	0.165
101	0.242	0.279	0.311	0.303	0.222	0.204	0.149
102	0.249	0.288	0.320	0.312	0.230	0.211	0.154
103	0.306	0.353	0.392	0.382	0.282	0.258	0.188
104	0.256	0.296	0.329	0.320	0.236	0.216	0.158

Table A3.6f: Tables of performance measures (severity) calculated

Pipe	32	32	33	33	35		
Node	**F1**	**F2**	**F1**	**F2**	**F1**		
1	0.116	0.268	0.242	0.275	0.281		
2	0.147	0.341	0.307	0.350	0.357		
3	0.116	0.268	0.242	0.275	0.281		
4	0.168	0.391	0.351	0.401	0.408		
5	0.136	0.315	0.284	0.323	0.330		
6	0.132	0.307	0.276	0.315	0.321		
7	0.184	0.426	0.384	0.437	0.446		
8	0.127	0.295	0.266	0.303	0.309		
9	0.154	0.330	0.322	0.330	0.330		
10	0.152	0.354	0.319	0.363	0.371		
11	0.136	0.315	0.284	0.323	0.330		
12	0.252	0.443	0.443	0.443	0.443		
13	0.114	0.264	0.238	0.271	0.276		
14	0.100	0.232	0.209	0.238	0.243		
15	0.109	0.254	0.228	0.260	0.265		
16	0.113	0.265	0.236	0.272	0.275		
17	0.111	0.260	0.232	0.267	0.270		
18	0.131	0.306	0.284	0.326	0.330		
19	0.106	0.248	0.226	0.259	0.263		
20	0.094	0.221	0.202	0.232	0.236		
21	0.103	0.240	0.215	0.246	0.250		
22	0.098	0.230	0.205	0.236	0.238		
23	0.110	0.256	0.231	0.263	0.268		
24	0.131	0.304	0.274	0.312	0.318		
25	0.193	0.420	0.403	0.420	0.420		
26	0.111	0.258	0.232	0.264	0.270		
27	0.162	0.375	0.338	0.385	0.392		
28	0.120	0.280	0.252	0.287	0.293		
29	0.139	0.324	0.291	0.332	0.339		
30	0.108	0.250	0.225	0.256	0.261		
31	0.143	0.333	0.300	0.342	0.348		
32	0.110	0.255	0.229	0.261	0.266		
33	0.109	0.253	0.228	0.260	0.265		
34	0.180	0.417	0.376	0.428	0.436		
35	0.139	0.322	0.290	0.330	0.336		
36	0.125	0.289	0.261	0.297	0.303		
37	0.149	0.330	0.311	0.330	0.330		
38	0.133	0.308	0.278	0.316	0.322		
39	0.127	0.295	0.266	0.303	0.309		
40	0.144	0.336	0.302	0.344	0.351		
41	0.119	0.278	0.250	0.284	0.290		
42	0.130	0.303	0.272	0.311	0.316		
43	0.130	0.302	0.272	0.310	0.315		
44	0.152	0.353	0.318	0.363	0.370		
45	0.133	0.310	0.278	0.318	0.323		
46	0.100	0.234	0.210	0.240	0.244		
47	0.120	0.281	0.252	0.289	0.293		
48	0.114	0.266	0.239	0.274	0.278		
49	0.103	0.240	0.215	0.246	0.250		
50	0.157	0.368	0.329	0.377	0.382		
51	0.111	0.258	0.231	0.265	0.269		

52	0.116	0.273	0.244	0.280	0.283			
53	0.126	0.295	0.273	0.314	0.318			
54	0.112	0.261	0.234	0.268	0.272			
55	0.096	0.225	0.201	0.231	0.234			
56	0.149	0.330	0.330	0.330	0.330			
57	0.112	0.261	0.239	0.274	0.278			
58	0.106	0.247	0.222	0.253	0.258			
59	0.132	0.308	0.276	0.316	0.321			
60	0.132	0.309	0.277	0.317	0.322			
61	0.116	0.273	0.242	0.281	0.282			
62	0.102	0.240	0.214	0.246	0.249			
63	0.131	0.305	0.273	0.313	0.318			
64	0.119	0.280	0.250	0.287	0.291			
65	0.111	0.259	0.249	0.285	0.290			
66	0.107	0.248	0.227	0.259	0.263			
67	0.140	0.328	0.294	0.336	0.342			
68	0.107	0.248	0.223	0.254	0.259			
69	0.103	0.241	0.215	0.247	0.251			
70	0.107	0.250	0.224	0.257	0.261			
71	0.105	0.244	0.219	0.250	0.254			
72	0.114	0.266	0.239	0.274	0.278			
73	0.104	0.245	0.217	0.251	0.253			
74	0.095	0.223	0.199	0.229	0.232			
75	0.099	0.232	0.207	0.238	0.241			
76	0.106	0.248	0.227	0.260	0.264			
77	0.100	0.232	0.209	0.238	0.242			
78	0.105	0.244	0.219	0.250	0.254			
79	0.155	0.330	0.323	0.330	0.330			
80	0.130	0.304	0.271	0.312	0.315			
81	0.130	0.304	0.271	0.312	0.315			
82	0.103	0.241	0.216	0.247	0.251			
83	0.110	0.257	0.230	0.264	0.268			
84	0.105	0.244	0.219	0.250	0.255			
85	0.103	0.240	0.215	0.246	0.250			
86	0.105	0.243	0.219	0.250	0.254			
87	0.130	0.304	0.271	0.312	0.315			
88	0.149	0.347	0.319	0.365	0.371			
89	0.124	0.290	0.270	0.309	0.314			
90	0.096	0.224	0.212	0.242	0.246			
91	0.106	0.247	0.222	0.253	0.258			
92	0.102	0.238	0.216	0.247	0.251			
93	0.136	0.320	0.296	0.330	0.330			
94	0.112	0.261	0.239	0.274	0.278			
95	0.116	0.268	0.242	0.275	0.281			
96	0.112	0.261	0.235	0.267	0.273			
97	0.113	0.261	0.235	0.268	0.273			
98	0.158	0.365	0.329	0.375	0.383			
99	0.189	0.420	0.395	0.420	0.420			
100	0.140	0.326	0.293	0.330	0.330			
101	0.130	0.303	0.272	0.311	0.316			
102	0.134	0.312	0.281	0.320	0.327			
103	0.165	0.382	0.344	0.392	0.399			
104	0.138	0.320	0.289	0.329	0.335			