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Model-free pressure control in water distribution networks

Thapelo Cornelius Moseitlhe

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Contrôle de la pression sans modèle dans les réseaux
de distribution d'eau
Model-free pressure control in water distribution networks

**Thèse de doctorat de l'université Paris-Saclay et de Tshwane University of
Technology**

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Mots clés : Contrôle de la Pression, Model-free, Réseau de Distribution d'Eau, Optimisation

Résumé : La gestion des réseaux de distribution d'eau (WDN) est critique pour la sécurité des ressources en eau. La variabilité climatique augmente la nécessité de gérer correctement les ressources disponibles. Une quantité importante d'eau est perdue dans les systèmes d'approvisionnement en eau en Afrique du Sud, et la quantité de ces pertes dépend principalement de la pression dans le système. Par conséquent, le contrôle de la pression dans les WDN est l'une des interventions couramment utilisées pour améliorer la fiabilité et la durabilité de l'approvisionnement en eau. Une pression excessive dans les systèmes d'approvisionnement en eau (WSS) augmente les pertes d'eau et les ruptures de tuyaux, ainsi que le besoin de réparations fréquentes. D'un autre côté, une pression inadéquate pourrait entraîner des flux entrants (infections) dans le système et/ou une non-livraison d'eau à l'utilisateur final. Cela pourrait entraîner une mauvaise santé pour l'utilisateur final et des problèmes socio-économiques dans la société.

En général, le problème de contrôle de la pression est résolu en installant des vannes de réduction de pression (PRV) dans les WDN et en déterminant leurs réglages appropriés. Diverses approches ont été proposées pour déterminer les paramètres appropriés. Des schémas de contrôle classiques, optimaux et avancés ont été utilisés. Ces méthodes reposent sur la précision d'un modèle afin de contrôler précisément un WDN réel. Par conséquent, toute variation entre les paramètres d'un modèle et d'un WDN réel pourrait rendre un schéma de contrôle inutile.

Ce projet de recherche propose l'utilisation de la technique d'apprentissage par renforcement (RL) pour contrôler les pressions sur les nœuds dans les WDN. Une approximation quadratique basée sur un émulateur de la simulation hydraulique est utilisée comme environnement interagissant avec l'agent RL. A partir de ces interactions, l'agent RL reçoit les données sur les pressions actuelles et propose ensuite les réglages de contrôle appropriés des PRV. Les performances du schéma proposé sont comparées au schéma d'optimisation conventionnel qui est couramment utilisé pour les cas de simulation. Les résultats montrent que le schéma proposé peut atteindre les résultats souhaités, par rapport à la procédure d'optimisation de référence. Trois études de cas étudiées sur des niveaux de charge de 100 % ont montré que l'application du schéma proposé pouvait entraîner une réduction d'au moins 10 % et d'au plus 33 % de la pression de refoulement. Une observation similaire car le schéma proposé est soumis à différents chargements pendant une période de vingt-quatre (24) heures. Cependant, contrairement à la procédure d'optimisation, le schéma proposé a obtenu les résultats sans la solution numérique des WDN. Par conséquent, ce schéma pourrait être applicable dans des situations où le modèle d'un réseau n'est pas bien défini.

Title : Model-free Pressure Control in Water Distribution Networks

Keywords : Optimisation, Water distribution networks, Model-free, Pressure Control

Abstract : Management of water distribution networks (WDNs) is critical for the security of water resources. Climate variability increases the need to properly manage the available resources. A significant amount of water is lost in water supply systems in South Africa, and the quantity of these losses depends mostly on the pressure in the system. Therefore, pressure control in WDNs is one of the interventions commonly employed to improve the reliability and sustainability of the water supply. Excessive pressure in water supply systems (WSSs) increases water loss and pipe breakages, and the need for frequent repairs. On the other hand, inadequate pressure could lead to inward flows (infections) into the system and/or non-delivery of water to the end-user. This could lead to ill-health for the end-user and to socio-economic issues in the society.

In general, the pressure control problem is addressed by installing pressure-reducing valves (PRVs) in WDNs and determining their appropriate settings. Various approaches have been proposed to determine the appropriate settings. Classical, optimal and advanced control schemes have been used. These methods rely on the accuracy of a model in order to precisely control a real WDN. Therefore, any variation between the parameters of a model and a real WDN could render a control scheme useless.

This work now proposes the utilisation of the reinforcement learning (RL) technique to control node pressures in WDNs. An emulator-based quadratic approximation of the hydraulic simulation is used as an environment interacting with the RL agent. From these interactions, the RL agent receives the data on current pressures and then proposes appropriate control settings of the PRVs. The performance of the proposed scheme is compared with the conventional optimisation scheme that is commonly used for simulation cases. The results show that the proposed scheme can achieve the desired results, when compared to the benchmark optimisation procedure. Three case studies investigated on 100 % loading levels showed that the application of the proposed scheme could result in at least 10 % and at most 33 % reduction in head pressure. A similar observation as the proposed scheme is subjected to different loading patterns for twenty-four (24) hours period. However, unlike the optimisation procedure, the proposed scheme achieved the results without the numerical solution of the WDNs. Therefore, this scheme could be applicable in situations where the model of a network is not well defined.

DEDICATION

I dedicate this work to those with positive contributions towards its completion.

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RÉSUMÉ

La gestion des réseaux de distribution d'eau (WDN) est essentielle pour la sécurité des ressources en eau. La variabilité climatique augmente la nécessité de gérer correctement les ressources disponibles. Actuellement, les services publics sont confrontés au défi de fournir de l'eau alors que la ressource se raréfie. Une quantité importante d'eau est perdue dans les systèmes d'approvisionnement en eau en Afrique du Sud, et la quantité de ces pertes dépend principalement de la pression dans le système. Par conséquent, le contrôle de la pression dans les WDN est l'une des interventions couramment utilisées pour améliorer la fiabilité et la durabilité de l'approvisionnement en eau. Une pression excessive dans les systèmes d'approvisionnement en eau (WSS) augmente les pertes d'eau et les ruptures de canalisations, ainsi que le besoin de réparations fréquentes. D'un autre côté, une pression inadéquate pourrait entraîner des flux entrants (infections) dans le système et/ou une non-livraison d'eau à l'utilisateur final. Cela pourrait entraîner une mauvaise santé pour l'utilisateur final et des problèmes socio-économiques dans la société.

En général, le problème de contrôle de la pression est résolu en installant des vannes de réduction de pression (PRV) dans les WDN et en déterminant leurs réglages appropriés. Diverses approches ont été proposées pour déterminer les paramètres appropriés. Des schémas de contrôle classiques, optimaux et avancés ont été utilisés. La plupart de ces méthodologies qui ont été proposées dans la littérature ont montré des résultats positifs. Cependant, il convient de noter que la plupart de ces schémas reposent sur la

précision d'un modèle afin de contrôler des systèmes physiques réels. Par conséquent, tout écart entre un modèle et le système réel pourrait conduire à un fonctionnement indésirable car un modèle ne serait pas une représentation exacte du système physique. Les éléments des WDN sont exposés à diverses conditions environnementales, il est donc inévitable que les paramètres du réseau (c'est-à-dire la résistance hydraulique) soient affectés. Cela peut entraîner une inadéquation entre les paramètres du modèle et le système physique. L'effet des conditions environnementales sur les paramètres du réseau n'a pas été précédemment pris en compte dans la littérature.

Ce travail propose maintenant l'utilisation de la technique d'apprentissage par renforcement (RL) pour contrôler les pressions sur les nœuds dans les WDN. Une approximation quadratique basée sur un émulateur de la simulation hydraulique est utilisée comme environnement interagissant avec l'agent RL. A partir de ces interactions, l'agent RL reçoit les données sur les pressions actuelles et propose ensuite les réglages de contrôle appropriés des PRV. Les performances du schéma proposé sont comparées au schéma d'optimisation conventionnel qui est couramment utilisé pour les cas de simulation. Les résultats montrent que le schéma proposé peut atteindre les résultats souhaités par rapport à la procédure d'optimisation de référence. Trois études de cas étudiées sur des niveaux de charge de 100 % ont montré que l'application du schéma proposé pouvait entraîner une réduction d'au moins 10 % et d'au plus 33 % de la pression de refoulement. Une observation similaire car le schéma proposé est soumis à différents schémas de chargement pendant une période de vingt-quatre (24) heures. De plus, les résultats montrent que les débits dans les tuyaux peuvent être réduits en utilisant ce schéma. La réduction des débits et de la pression nodale conduit à des débits de fuite réduits du système. Il a été constaté que le pourcentage de réduction le plus élevé culminait à 10,64 % pour un nœud directement connecté au PRV. De plus, pour les nœuds éloignés des PRV, une réduction minimale des fuites de 1,71 % a été enregistrée. Cependant, contrairement à la procédure d'optimisation, le schéma proposé a atteint les résultats

sans la solution numérique des WDN. Par conséquent, ce schéma pourrait être applicable dans des situations où le modèle d'un réseau n'est pas bien défini.

ABSTRACT

Management of water distribution networks (WDNs) is critical for the security of water resources. Climate variability increases the need to properly manage the available resources. A significant amount of water is lost in water supply systems in South Africa, and the quantity of these losses depends mostly on the pressure in the system. Therefore, pressure control in WDNs is one of the interventions commonly employed to improve the reliability and sustainability of the water supply. Excessive pressure in water supply systems (WSSs) increases water loss and pipe breakages, and the need for frequent repairs. On the other hand, inadequate pressure could lead to inward flows (infections) into the system and/or non-delivery of water to the end-user. This could lead to ill-health for the end-user and to socio-economic issues in the society.

In general, the pressure control problem is addressed by installing pressure-reducing valves (PRVs) in WDNs and determining their appropriate settings. Various approaches have been proposed to determine the appropriate settings. Classical, optimal and advanced control schemes have been used. These methods rely on the accuracy of a model in order to precisely control a real WDN. Therefore, any variation between the parameters of a model and a real WDN could render a control scheme useless.

This work now proposes the utilisation of the reinforcement learning (RL) technique to control node pressures in WDNs. An emulator-based quadratic approximation of the hydraulic simulation is used as an environment interacting with the RL agent. From these interactions, the RL agent receives the data on current pressures and then proposes

appropriate control settings of the PRVs. The performance of the proposed scheme is compared with the conventional optimisation scheme that is commonly used for simulation cases. The results show that the proposed scheme can achieve the desired results, when compared to the benchmark optimisation procedure. Three case studies investigated on 100 % loading levels showed that the application of the proposed scheme could result in at least 10 % and at most 33 % reduction in head pressure. A similar observation as the proposed scheme is subjected to different loading patterns for twenty-four (24) hours period. However, unlike the optimisation procedure, the proposed scheme achieved the results without the numerical solution of the WDNs. Therefore, this scheme could be applicable in situations where the model of a network is not well defined.

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ACRONYMS

ANN Artificial Neural Network

CN Critical Node

GA Genetic Algorithm

IPOPT Interior Point Optimiser

MFC Model-free Control

MINLP Mixed-Integer Non-Linear Problem

MPC Model Predictive Controller

NLP Non-Linear Programming

PAT Pumps as Turbine

PCD Pressure Control Device

PCV Pressure Control Valve

PID Proportional-Integral-Derivative

PRD Pressure Reducing Device

PRV Pressure Reducing Valve

RL Reinforcement Learning

SCADA Supervisory Control and Data Acquisition Systems

WDN Water Distribution Network

WDS Water Distribution System

WSS Water Supply System

CHAPTER 1. INTRODUCTION

Never before have the requirements for reliable and dependable water distribution systems been so tight. Modern-day water distribution networks (WDNs) operate under many adverse dynamic conditions and yet they must meet the demands of an ever-increasing number of consumers for water of acceptable quality. Inter-connection of WDNs across cities and provinces has been done to augment supply and meet the increasing demand. These inter-connections have increased the complexities of the network, rendering the WDNs vulnerable to any mismanagement of the system.

It is reported that changes in climate in South Africa are decreasing the availability of water. Presently, utilities are faced with the challenge of supplying water from diminishing reserves. Figure 1.1 shows the scarcity index of water in South Africa. It can be seen that the south-western part of the country is water-stressed as a result of overuse of surface water. Proper operation and maintenance of water distribution systems (WDSs) is essential to ensure the reliability of the infrastructure ([Sankar et al., 2012b](#)) and sufficient supply ([De Corte & Sørensen, 2013](#)). Absent proper operation and maintenance, the integrity of WDSs will decline and compromise both supply and quality of water. This will pose a risk to the health of the consumers. Municipalities and suppliers will also experience financial losses due to non-revenue water lost from degrading WDSs. The clear implication of all this is that proper monitoring of the operation of the WDSs must be done, so that prompt corrective action is taken to improve the reliability of the

infrastructure.

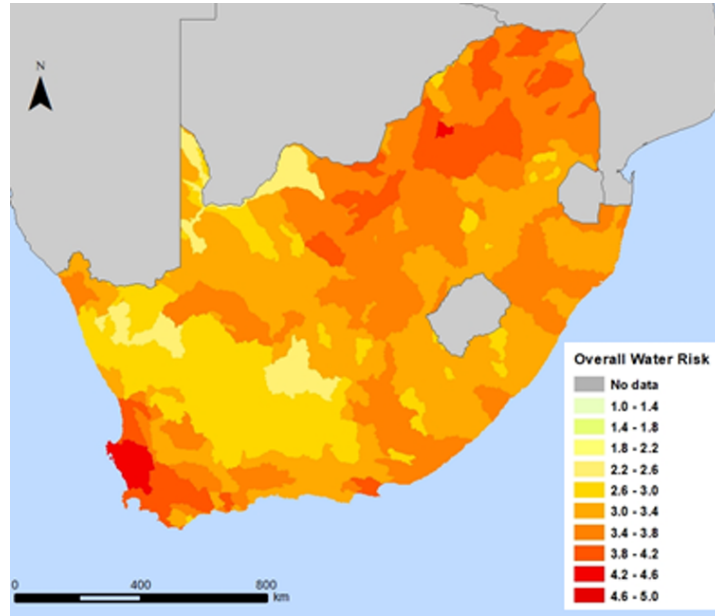


Figure 1.1: South Africa’s water stress index relative to global scores.

Presently, it is accepted that proper management of pressure in water distribution networks could contribute immensely to their reliability. Excessive pressure in WDNs degrades the quality of the network. The strength of the joints is affected, leading to loss of water through leakages. Equation 1.1 shows the relationship between the pressure head and the leakage flow.

$$q_i = \alpha h_i^p \quad (1.1)$$

In Equation 1.1, q is the leakage flow and α is the leakage discharge coefficient (Adedeji et al., 2017c). The pressure is represented by h while p represents the pressure exponent. It is evident that the relationship between the leakage flow and the system’s pressure is directly proportional. Some of the leakage orifices are depicted in Figure 1.2.



Figure 1.2: Damaged leaky pipe.

1.1 Motivation

It is evident that accurate pressure control in WDNs could reduce their inevitable losses. It is reported in (USEPA, 2010) that the water loss volume may amount to 30 % of the supplied quantity. Furthermore, in South Africa, the financial loss as a result of leakages amounts to about 7 billion ZAR (Adedeji et al., 2017b). Losses result largely from pressure mismanagement. This research uses simulation test cases to implement the proposed model-free pressure control scheme. The scheme that is being put forward intends to simplify computational issues associated with pressure-control schemes.

1.2 Problem Statement

In water distribution networks, unattended excessive pressure substantially contributes to the deterioration of the systems. In some cases, it degrades the bond of joints and thereby creates a path for water loss. Numerical optimisation of pressure in WDNs has shown great promise, but the computational complexity has resulted in calls for further investigation. This present study addresses the problem by developing a system of pressure control that uses measurements taken only on the critical nodes of the WDNs.

This system does not depend on accurate modelling of the WDN and circumvents the complex computations.

1.3 Sub-problems

Based on the problem statement, two sub-problems are identified.

1.3.1 Sub-problem 1

The first sub-problem concerns the development of the emulator for the hydraulic model that incorporates pressure reducing devices (PRDs).

Several authors have proposed solutions to the hydraulic model of WDNs ([Hamam & Brameller, 1971](#); [Todini & Pilati, 1988](#); [Piller et al., 2003](#); [Todini, 2008](#)). However, these methods are based on solving a set of non-linear equations through some sort of iterative procedures. Any perturbation to the WDN model, such as incorporating PRDs, may degrade the performance of the iterative procedures. In this work, a quadratic approximation of a consolidated WDN model is proposed to address the solution of a hydraulic model that incorporates PRDs.

1.3.2 Sub-problem 2

The second sub-problem deals with the development of a model-free system for pressure control in WDNs.

The computational complexities associated with hydraulic simulation are well known ([Hamam & Hindi, 1992](#)). Embedding the optimisation solution for pressure control increases the complexity. This work proposes the utilisation of machine learning techniques to avoid the complexities associated with numerical solutions.

1.4 Purpose and Aims

In order to mitigate excessive pressure in WDNs, the purpose of this work is, therefore:

- To formulate a mathematical technique to emulate the model-based hydraulic simulation with the incorporation of pressure control devices
- To identify and evaluate alternative techniques that are suitable for pressure control in WDNs
- To develop a quasi-steady-state model-free control scheme for pressure in WDNs.

Additionally, this work would offer some contributions in the following domains:

- Identification of critical nodes in water supply systems
- Leakage minimisation in water distribution networks.

1.5 Contribution of the study

During the course of this research, the following contributions have been made.

Firstly, the utilisation of alternative schemes to hydraulic simulation based on the historical behaviour of the network has been reported in:

- **T. C. Mosetlhe**, Y. Hamam, S. Du, E. Monacelli and Y. Alayli. 2019. Water Distribution Networks Model Identification using Artificial Neural Networks. In: Proceedings of AFRICON 2019, Accra, Ghana, pp. 1 - 5, IEEE.

A major challenge in optimal pressure control in WDNs is the computational complexities associated with the hydraulic simulation and its perturbation when PCDs are added. This stems from the non-linearities of both the hydraulic model and the PCDs. In addition, the solution of the non-linear optimisation problem set-up to determine the optimal settings adds to the complexities. Schemes have been proposed to deal with the computational complexities of both the hydraulic simulation and control schemes. So a second contribution to the field is a journal paper titled

- **T. C. Mosetlhe**, Y. Hamam, S. Du, E. Monacelli, and A. A. Yusuff. 2020. Towards Model-Free Pressure Control in Water Distribution Networks. *Water*, 12 (10), pp 2697, MDPI.

Identification of critical nodes for measurement is imperative in the management of the WDNs. This is as a results of costs that may be incurred in the acquisition of measuring equipments and their subsequent deployment in the networks. Consequently this work put forward a suboptimal greedy algorithm to identify critical nodes in the network. This is reported in the publications as listed:

Journal Article(s)

- **T. C. Mosetlhe**, Y. Hamam, S. Du, and E. Monacelli. Appraising the Impact of Pressure Control on Leakage Flow in Water Distribution Networks: Model-free Approach. *Water*, 12 (6), p.1732, MDPI.

Conference Paper(s)

- **T. C. Mosetlhe**, Y. Hamam, S. Du, and E. Monacelli. Identification of Critical Nodes in Water Distribution Networks. *Accepted for publication in the International Symposium on Water, Ecology and Environment (ISWEE)*

In addition, several papers have been published, as listed below, in the course of this research.

Journal Article(s)

- **T. C. Mosetlhe**, Y. Hamam, S. Du, and E. Monacelli. 2020. A Survey of Pressure Control Approaches in Water Supply Systems. *Water*, 12 (6), pp 2697, MDPI.

Conference Paper(s)

- **T. C. Mosetlhe**, Y. Hamam, S. Du, and Y. Alayli. 2018. Artificial neural networks in water distribution systems: A literature synopsis. In: Proceedings of 2018 International Conference on Intelligent and Innovative Computing Applications, Plaine Magnien, Mauritius, pp. 1 - 5, IEEE.
- **T. C. Mosetlhe**, Y. Hamam, S. Du, and E. Monacelli. Modelling and Analysis of Leakages for Multi-Periods in Water Distribution Networks. *In progress*

1.6 Thesis Layout

The layout of the thesis is as follows:

- Chapter 2 Presents a literature review of research and developments in the area of pressure control in WDNs. Various control strategies are presented with their pros and cons.
- Chapter 3 The mathematical model of the WDN is presented. In addition, the pressure reducing model used in the course of research is also furnished. The optimisation formulation adapted from the literature is also presented in this chapter. Finally, the proposed scheme for pressure control and the applied algorithm is given.
- Chapter 4 A greedy algorithm for the identification of critical nodes is put forward in this chapter. Mathematical formulation forming the core of the algorithm are given. Two case studies are used to evaluate its appropriateness.
- Chapter 5 This chapter presents the application of the proposed scheme in three test cases. The performance of the proposed scheme is compared to the classical optimisation methods. This is done on three different loading levels. The results of these applications are presented in this chapter.
- Chapter 6 In this chapter, the applicability of the proposed model-free scheme is tested in a multi-period scenario.
- Chapter 7 A summary of the work done in the dissertation is presented in this chapter. Furthermore, the concluding remarks of the study and suggestion for future works are provided.

CHAPTER 2. REVIEW OF LITERATURE

2.1 Introduction

This chapter presents the literature reviewed for the purpose of this research. Pressure control schemes are classified into five broad categories. Advantages and disadvantages of these schemes are presented. Summaries are put forward in tabular forms for the benefit of the reader.

2.2 Background

The bulk potable water supply network consists of reservoirs, pipes, and demands. The networks transport the water generally stored in the reservoir to the consumers. Geographically, water distribution networks (WDNs) are vast and interconnected. The effectiveness of water transportation depends primarily on the state of the networks' components. For example, a broken pipe may result in partial or complete non-delivery of water to the intended consumers. Unfortunately, the increasing level of urbanization increases the vulnerability of WDN components and, therefore, increases the complexities in their operation (Bello et al., 2019; Adedoja et al., 2018).

Such complexities give rise to various abnormalities in the networks. Predominantly, these abnormalities are issues that must be dealt with in the short term. For instance,

varying consumer demand compels the operator to adjust the pressure in the network continuously to ensure that adequate levels of supply are achieved and water is effectively delivered. To deal with this need, pumps and pressure-reducing valves (PRVs) are often installed in the network; they are adjusted as the demand changes. The engineering problem is how to ensure proper control of such devices.

2.3 Pressure Control

Pressure control in water supply systems is a well-studied method of minimising leakage ([Hindi & Hamam, 1991b,c](#); [Puust et al., 2010](#); [Gupta et al., 2016](#)). Notable works on this subject can be found from the early 1990s. ([Hindi & Hamam, 1991b,c](#)). [Hindi & Hamam \(1991b\)](#) explored the utilization of constant-outlet-pressure valves and flow-modulated valves for loss minimization in WDNs. However, the excessive computational burden prompted [Hamam & Hindi \(1992\)](#) to utilize artificial neural networks to control the pressure. Reduced losses are observed subsequent to the implementation of this scheme. [Dai & Li \(2014\)](#) presented an extended model for PRVs to enable the three-mode (open, normal and check valve) operation in water distribution networks for loss minimization without violating the constraints. This formulation was found to be beneficial when tested under several demand scenarios. In ([Gupta et al., 2016](#)), a multi-objective strategy was formulated for pressure control and effectively reducing losses in WDNs. Under steady-state operation, the formulated strategy yielded a 6.15 L/s reduction in losses.

Although pressure control via PRVs yields satisfactory results, the energy loss as a result of head loss by dissipation is a significant concern ([Lima et al., 2017, 2018](#)). This affects the overall energy efficiency as the energy that could otherwise be converted into a useful form is dissipated. The utilization of PRVs jointly with pumps was proposed in

([Shao et al., 2019](#)) to improve the energy utilization of WDNs. The joint scheduling of pressure control and energy recovery based on the demand showed a reduction in both leakages and the consumption of electrical energy at pumping stations. In recent times, pumps as turbines (PATs) are being used as a solution for hybrid pressure control and energy recovery. In ([Alberizzi et al., 2019](#)), the speed and pressure control of PATs were investigated. The maximum energy recovered in the work was 23%. To select appropriate and cost-effective applications, PATs were put forward in ([Marchiori et al., 2019](#); [García et al., 2019](#)).

2.3.1 Pressure Control Devices

Various pressure control devices are available for different purposes. Their deployment in water distribution networks depends on a specific need that arises. They may be used to control, limit, maintain, or break water pressure, in the pipe or a node of the network. Table [2.1](#) shows different types of such devices and their specific use.

Table 2.1: Pressure control elements.

Element	Use
Pressure reducing valves (PRV)	Regulation of pressure when and if it exceeds the pre-set values
Pressure sustaining valves (PSV)	Sustain a certain specified pressure value
Pressure control valves (PCV)	Control the pressure in the identified pressure management area
Pressure breaker valve (PBV)	Force and maintain specified pressure loss across the valve
Pumps as turbines (PATs)	Regulation of pressure when and if it exceeds the pre-set values and the recovery of energy.

In general, PRVs are mostly used when the problem of excessive pressure arises with the reduction of the demand in the network (Puust et al., 2010). However, in recent times, due to constraints on energy supply, PATs have been used to recover that excess head loss and convert it into useful energy (Camilo Rosado et al., 2020; Fernández García & Mc Nabola, 2020). The correct placement of these devices is as important as their control function to ensure that an overall reduction in pressure is achieved (Eck & Mevissen, 2012) at a minimum operating cost.

2.3.2 Placement of Pressure Control Devices

Various methods have been put forward in the literature to solve the problem of the placement of PRVs. These methods could be classified into three broad categories, namely (1) the enumerative method, (2) the pressure reference method, and (3) calculus-based/optimization methods.

2.3.2.1 Enumerative Method

In this method, several valves are randomly inserted into the water distribution network. Optimization techniques that will eventually result in their optimum settings are applied. This method requires significant computational effort to reach the optimum solution; however, it is easier to apply. The work in (Jowitt & Xu, 1990) used successive linearisation on flow equations of nodal heads and pipes to be able to use linear programming to solve the valve control problem. Three valves were inserted on a 25-node, 37-pipe network. The results obtained showed that the optimization problem took between 8 and 15 iterations to yield the optimal solution.

2.3.2.2 Pressure Reference method

This class of methods is based on hydraulic simulation. The reference pressure is identified, and hydraulic simulations are performed under different demand conditions. This method was proposed by Liberatore & Sechi (2009). For all demand patterns, the installation sites are selected as pipes that satisfy Rule 1.

$$\text{Rule1 :if } h_i > h^{ref} \text{ and } h_j < h^{ref}$$

Pipe is selected as a PRV installation site.

Nonetheless, the work in (Gupta et al., 2016) concluded that the method suffered from

the drawback that it would not consider the pipes whereby both $h_i > h^{ref}$ and $h_j > h^{ref}$ and their difference was slightly higher. Therefore, this was mitigated by the introduction of the rule that aimed to check the difference $h_i - h_j$ and considered the pipe if it was found to be above the threshold. Rule 2 was then incorporated into the methodology proposed by [Liberatore & Sechi \(2009\)](#).

$$Rule2 : \text{if } h_i - h_j > 0.1 \times h^{ref}$$

Pipe is selected as a PRV installation site.

Further improvement on the pressure reference method was proposed in [Gupta et al. \(2020\)](#). This recent improvement leveraged the nodal matrix analysis to enable the scheme to be applicable to large-scale networks.

2.3.2.3 Calculus-Based/Optimisation Methods

This class of methods was first considered in ([Hindi & Hamam, 1991a](#)) for the placement of PRVs. They proposed a scheme based on minimisation of installed valves while minimising the pressure in the systems. The resultant mixed-integer non-linear programming was linearised to realise an efficient computational scheme to solve the problem. The work in ([Eck & Mevissen, 2012](#)) formulated the problem as a mixed-integer non-linear optimisation problem (MINLP). The authors proposed an approximation for pipe head loss, and their proposed approach compared favourably to EPANET. The interior point optimizer (IPOPT) was used in ([Dai & Li, 2014](#); [Dai, 2018](#)) to solve their hybrid localisation and control problem formulated as the MINLP. Their formulation aimed to reduce the number of valves while also reducing the pressure in the network. Reduced pressure was observed after the solving of their problem scheme. The dual problem was further studied and solved using their genetic algorithm (GA) ([Nicolini & Zovatto, 2009](#); [Nicolini, 2011](#)). However, earlier in ([Hindi & Hamam, 1993](#)), a conclusion was reached

that GA did not seem to offer any advantage as compared to solving the integer problem directly. Research on strategies to place PATs is yet to be harmonised, with a handful of works having been published. The work in (Coelho & Andrade-Campos, 2018) proposed the utilisation of numerical decision support tools to select sites for PATs optimally. This scheme was based on an optimisation problem formulated to maximise the potential recoverable energy. A dual objective function was formulated in (Lima et al., 2017) to maximise the energy recovered and leakage volume reduction. Particle swarm optimisation was selected to solve the optimisation problem and determine optimal sites for PATs.

The pros and cons of the three classes of methods are presented in Table 2.2. It is worth noting that these calculus-based methods gave the optimal method at a high computation cost as compared to the enumerative method and pressure reference method.

Table 2.2: Brief summary of classes of methods for the placement pressure reduction valves in water distribution networks.

Method	Pros	Cons
Enumerative method (Jowitt & Xu, 1990)	Easier to apply	Optimal placement and numbers of PRVs cannot be guaranteed
Pressure reference method (Liberatore & Sechi, 2009 ; Gupta et al., 2016, 2020)	Less computational burden	Optimal placement of PRVs cannot be guaranteed
Calculus-based/optimization methods (Hindi & Hamam, 1991a, 1993 ; Nicolini & Zovatto, 2009 ; Nicolini, 2011 ; Eck & Mevissen, 2012 ; Dai, 2018 ; Coelho & Andrade-Campos, 2018 ; Lima et al., 2017)	Optimal placement, numbers of PRVs can be guaranteed	Computationally demanding

2.3.3 Pressure Control Techniques

Various control strategies have been developed for pressure management in water distribution networks, and advances in control strategies have improved the ability to manage

the operation and efficiency of WDNs. In general, control strategies deployed in pressure control in WDNs are based on the following principles, which were reported in (Adedeji et al., 2018a).

1. Fixed outlet pressure control
2. Time-modulated pressure control
3. Flow-modulated pressure control
4. Closed-loop pressure control
5. Optimal pressure control

Currently, efforts are geared towards real-time control schemes (Shamir & Salomons, 2008; Laucelli et al., 2016). This trend of activities has led to the necessity to improve the schemes such as the expert-based one proposed in (Coulbeck et al., 1996). In the said expert-based scheme, pressure measurement points were defined as the state variables of the systems, while the consumer demand points were the disturbance to the system. The control variables of the expert system were the individual pumps at the pump station. The control strategy employed is shown in Algorithm 1 where *condition* is the sequence of logic comparison operation and *conclusion* is the sequence of assignments to control variables.

Algorithm 1: Expert System Control Rule

Data: System measurements.

Result: Decision for system control

```
1 Initialization;
2 while System in operation do
3   | get measurements;
4   | if condition is satisfied then
5   |   | conclusion;
6   | else
7   |   | get measurements;
8   | end
9 end
```

The work on the logic controller was further expanded to develop constant pressure water supply (Yang et al., 2010). The programmable logic controller in conjunction with a frequency converter was used to achieve constant pressure water supply. The drawback of this system is that water demand is not constant. Therefore, by applying constant pressure on the system, there existed a possibility of excessive or insufficient pressure in the network.

In general, the most common control techniques applied for pressure regulation may be classified into five broad categories as shown in Figure 2.1.

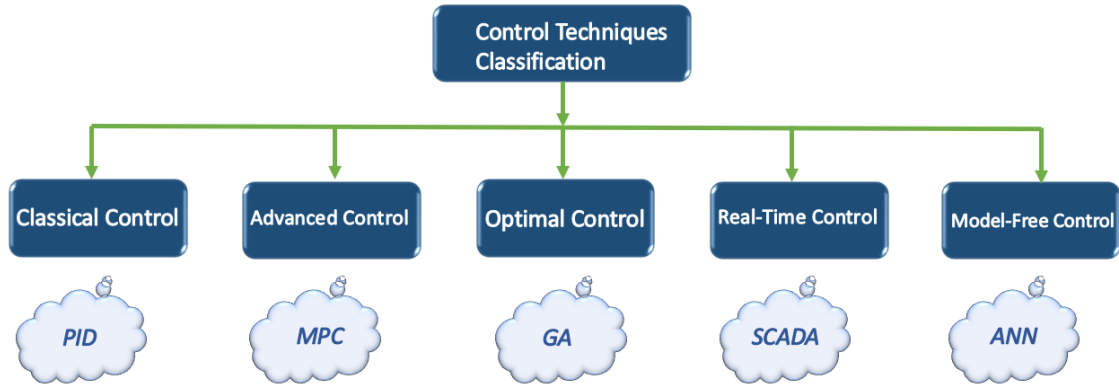


Figure 2.1: Classification of control techniques.

2.3.3.1 Classical Control Strategy

Classical control methods are based on one-at-a-time parameter control (On-Off) or proportional-integral-derivatives (PID) controllers. Their application could be appropriate for small-scale systems; however, they may still be applied in WDNs. The PID controller is a common strategy for different industrial processes. In (Page et al., 2016), the parameterless P-controller was proposed. The P controller proposed was based on the trial and error method for tuning of the gain parameter K_o . The classical PID controller was proposed by Lei & Jing (2007) to control the pumping system in WDN for pressure regulation. However, concerns about its control precision and capability were raised in (Wang & Wang, 2009). The issue of frequency fluctuations that may lead to unsteady pressure in the pipeline was also raised in Peng et al. (2009). The work in (Prescott & Ulanicki, 2008) proposed a PID to control the PRV to improve the response of the system under transients. The proposed scheme showed improvement in network response.

2.3.3.2 Advanced Control Strategies

As systems such as WDNs are becoming more complex, advanced control strategies with the capability of controlling several parameters at the same time may be appropriate. To advance the work done by [Yang et al. \(2010\)](#), a two-dimensional fuzzy controller was proposed in ([Peng et al., 2009](#)). The deviation between a pre-determined and measured pressure in WDN was the input to the controller, and the output was the control system commands. The fuzzy-based system was also used for operational optimisation in ([Bezerra et al., 2012](#)). By using these systems, valve opening and control of the pumping system were achieved. Nevertheless, it is imperative that the pre-determined pressure be adjusted as the demand in a WDN varies.

Fuzzy PID controllers were also exploited for pressure management in ([Wang & Wang, 2009](#)). Inputs to the fuzzy PID controller were the error e and change in error de/dt , as shown in [Figure 2.2](#). The self-adaptive gain parameters K_p , K_i , and K_d were used by the controller to find a relationship between PID parameters and input parameters.

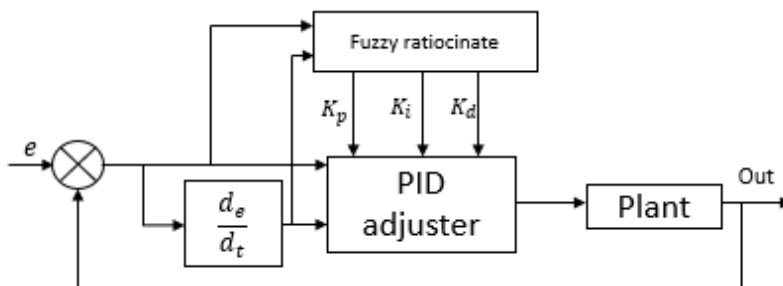


Figure 2.2: Basic model predictive scheme ([Wang & Wang, 2009](#)).

Adaptive reference control was proposed in ([Liberatore & Sechi, 2009](#); [Kallesoe et al., 2015](#)) to achieve constant pressure at the critical nodes of the system. Various authors have proposed model predictive control (MPC) for pressure management in WDNs. To a great degree, MPC has been a useful control technique in various industrial processes.

This is due to its ability to re-develop a control problem into an optimisation problem (Bello et al., 2014) and its usefulness in real-time application (Zeilinger et al., 2014; Bangura & Mahony, 2014). Figure 2.3 shows the basic MPC proposed by Sankar et al. (2012a). The proposed scheme used the pressure-driven model to simulate the dynamics of the WDN.

From the measurements that were taken in the WDN flow rate, pressure and outflow rate were estimated (Kumar, 2008) and integrated with the optimiser. The optimiser found the optimal pressure settings by minimizing the objective function:

$$\begin{aligned}
 & \text{minimize} && f(q) \\
 & \text{subject to} && 0 < u_k < 1 \\
 & && h_i \geq h^{min}
 \end{aligned} \tag{2.1}$$

where u_k is the PRV control position index, h_i is the pressure associated with node i , h^{min} is its minimum pressure allowed, and q is the flow in the pipe. An improved MPC was designed by Sankar et al. (2015) with an improved predictor model. In their earlier work, an extended period simulation was used as the predictor model. However, in the latter work, a quasi-steady-state model was used. In (Robles et al., 2016), a reliable fault-tolerant MPC was proposed. The design of the controller was done such that, after a fault occurred, the optimization and predictive capability was not affected.

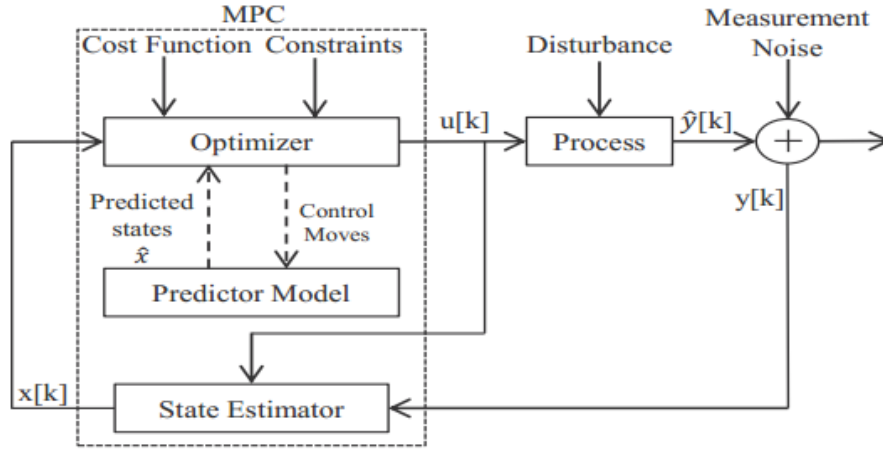


Figure 2.3: Basic model predictive scheme (Sankar et al., 2012a).

2.3.3.3 Optimal Control

Optimal pressure control in a water distribution network is desired to ensure the minimisation of leakages (Jose & Sumam, 2016). Often, the optimization is formulated to minimise the pressure under multiple demands (Nicolini & Zovatto, 2009; Nicolini et al., 2010; Pecci et al., 2015). The work in (Hindi & Hamam, 1991b) formulated the pressure reduction problem as a non-linear, non-convex optimisation problem. Two separate programming schemes were proposed to approximate non-linearly as an approximated linear programming problem. Their approach saw an improvement in computational efficiency in obtaining the solution. Recently, in (Oikonomou et al., 2018), the same strategy was applied to enable the response to different demand schedules. In (Eck & Mevissen, 2012), the problem of optimal pressure control by proposing the quadratic approximation of the pipe friction was addressed. The resultant non-linear problem was linearised, and the obtained solution showed a 1% deviation when compared to the commonly used EPANET (Rossman et al., 2000). It is worth noting that the linearisation of the problem would ultimately reduce the accuracy of the solution.

The problem of pressure control in WDNs was solved as a non-linear optimisation problem in (Vasudevan, 2018). It was observed that the increment of PRVs in the network resulted in the increased computational burden required to solve the problem. The interior point optimizer (IPOPT) was used in (Dai & Li, 2014; Dai, 2018) to solve the MINLP problem for pressure control. A decrease in pressure was observed, and the optimiser took ≈ 4.93 seconds. Strictly feasible sequential convex programming for control of pressure reducing valves was proposed in (Wright et al., 2015). The proposed methodology was used to solve the formulated NLP problem. The results showed a reduction of 3.7% in pressure. An MINLP problem was formulated to maximise the recovered energy and control the pressure in the WDN Corcoran et al. (2016). The scheme was tested on a 25 node benchmark test case. The results in (Corcoran et al., 2016) showed that optimisation could aid decision making in the installation of PATs.

Some researchers have favoured the utilisation of meta-heuristic techniques to solve pressure control problems. Conventional genetic algorithms (GA) were used to find optimal pressures in WDN (Araujo et al., 2006). The algorithm searched for a solution using adaptive mechanisms, and it was non-deterministic. The work in (El-Ghandour & Elansary, 2019) used a GA to solve the optimisation of the PRV problem, formulated as the minimisation of the difference between the maximum and the minimum pressure in the WDN. Their results showed that it was possible to control the abnormal surges in pressure by the optimal setting of the PRV parameters. The work in (Van Dijk et al., 2008) incorporated the weighted penalty in the GA in order to optimise the operation of the WDNs. The optimization procedure for energy recovery and leakage reduction utilising GA was developed in (Bonthuys et al., 2020). The objectives of the optimisation procedure were set to maximise the amount of energy recovered and the percentage of loss reduction. In (Cimorelli et al., 2018), a hybrid genetic algorithm was used to solve derivative-free non-linear programming for the optimal setting of PATs

for pressure control. The results showed that the scheme was able to maximise the energy produced by PATs. A non-dominated sorted genetic algorithm was used in (Nicolini, 2011; Gupta et al., 2016; Saldarriaga & Salcedo, 2015) to solve the multi-objective optimisation problems. The optimisation problems were formulated to reduce the number of valves used and to also determine their optimal operation. However, since these were heuristic approaches, global optimality could never be guaranteed.

A music-inspired approach was to obtain the optimal setting of the PRVs in De Paola et al. (2017). This methodology showed improved performance as compared to the genetic algorithms. The technique showed computational time and leakage reductions. Another scheme that showed a reduction in computational effort was the tabu-search metaheuristic approach proposed in (Fanni et al., 2000).

2.3.3.4 Real-Time Control

Research investments in real-time control of pressure in WDN have been gaining momentum recently (Creaco & Franchini, 2013; Page et al., 2016). In contrast to pressure settings during the operation of the network, these methods aim to determine the best pressure setting from continuous measurements that are taken. From the measurements, the pressure control devices (PCDs) in WDNs are adjusted appropriately taking into account the demand that must be met. Real-time pressure control strategies may be based on classical or advanced control strategies.

The work in (Creaco & Franchini, 2013) proposed a logic control algorithm to mitigate excessive and insufficient pressure that may exist in the network. Their control strategy assumed that a desired set-point value of piezometric height h_{sp} was known. The deviation of piezometric height $h(t)$ from the set-point was then used to calculate the variation $\Delta a(t)$ of closure setting a of the valve.

Remote real-time control of the pressure control valve (PCV) is currently an advanced method of pressure management in WDN (Page et al., 2016; Laucelli et al., 2016). This technique enables data to be collected from all the nodes in the network including isolated/remote nodes. Proportional (P) controllers were used in (Page et al., 2017b, 2016, 2017a), while in (Laucelli et al., 2016), programmable logic control was used to achieve remote real-time pressure control. Integral controller (I) $C(s) = \frac{K_i}{s}$ was used in (Fontana et al., 2017) to regulate the pressure by controlling PRVs in WDN. Laboratory experiments were used to validate the capability of the said controller.

Supervisory control and data acquisition systems (SCADA) (Cheng et al., 2014) in conjunction with a genetic algorithm were proposed in (Shamir & Salomons, 2008; Kang, 2014) to ensure that the pressure levels were maintained within acceptable limits. The proposed scheme was used in real time with application to WDN.

2.3.3.5 Model-Free Control

Model-free control (MFC) is a concept that encapsulates techniques often employed to control complex systems by using the ultra-local model of the network (simplified representation) (Sira-Ramírez et al., 2018). An MFC scheme does not need an explicit solution of the model to control the manipulated variables of the systems. In general, MFC schemes are employed to avoid complex computations that are related to the non-linear system, which are often expensive to evaluate (Sira-Ramírez et al., 2018). Hamam & Hindi (1992) proposed leveraging the ability of neural nets (NN) to describe non-linearity and developed an emulator for an optimisation procedure. This showed a reduced computational burden to control the PRV for pressure minimisation, and a substantial reduction in leakage was also observed. The approach adopted in (Rao & Alvarruiz, 2007; Rao & Salomons, 2007) was to mimic the hydraulic solution of WDNs. The resultant emulator was then coupled to a GA to determine the appropriate settings

of the PRVs. Though the schemes (Hamam & Hindi, 1992; Rao & Alvarruiz, 2007; Rao & Salomons, 2007) were able to control PRVs without an explicit solution of the hydraulic model, any change in the topology of the system would render them obsolete.

2.3.4 Effects of Pressure Control

It has been reported that issues of leakages and contamination in WDNs are mainly due to pressure mismanagement and pipe deterioration (Nicolini, 2011). At low pressures, through inwards leakages, infections that lead to contamination are introduced in the WDN. At high pressure conditions, the amount of water lost due to leakage increases significantly (Nicolini, 2011; Gupta et al., 2016). Therefore, pressure control could contribute towards the minimisation of the reported issues.

2.4 Application of Artificial Neural Networks in WDNs

Although Artificial Neural Networks ANNs have been used for pressure control, there exist several other applications in water distribution network that explored the utilisation of this technique.

2.4.1 ANN in Modelling Water Distribution Network (WDN)

Mathematical models of water distribution networks are widely available in the literature as systems of equations representing the nodal balance and the energy conservation of the pipes. Such equations are recalled in Chapter 3. In the early 90s, Hamam & Hindi (1992) applied ANN to map the hydraulic behaviour of non-linear WDNs with backpropagation used as the training algorithm. The structure of ANN used in (Hamam & Hindi, 1992) is shown in Figure 2.4 and for the inputs x_i and the weight ω_i , the output of neuron i

can be expressed as (2.2) (Hamam & Hindi, 1992; Rao & Alvarruiz, 2007)

$$y_i = f \left(\sum \omega_i x_i \right) \quad (2.2)$$

where

$$f(y_i) = \frac{1}{(1 + e^{-ay_i})} \quad (2.3)$$

and a is a constant used to control the slope of semi-linear regions (Huiqun & Ling, 2008). The suitability of ANNs in real-time water distribution is recognised by Rao & Salomons (2007). The Potable Water Distribution Management (POWADIMA) research project proposed multi-layer, feed-forward to mimic the operation of WDN (Rao & Salomons, 2007; Jamieson et al., 2007; Rao & Alvarruiz, 2007). More recently, flow dynamics of the water distribution network were forecasted using multi-layer feed-forward back-propagation ANN with up to 99 % confidence (Makaya & Hensel, 2015). It is worth noting that for successful replications, a large number of off-line simulations with different input combinations are required (Jamieson et al., 2007).

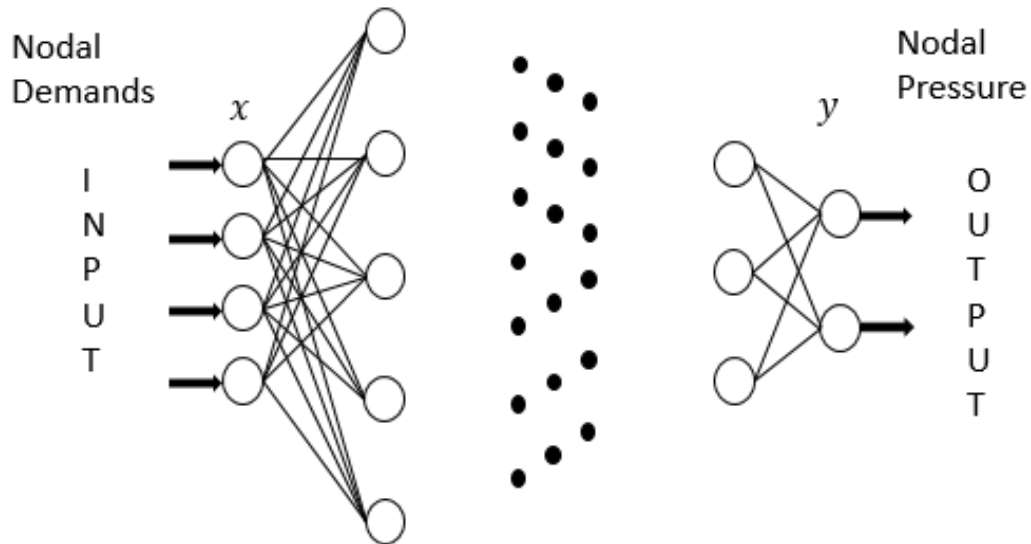


Figure 2.4: Structure of ANN with multiple hidden layers

2.4.2 ANN in Leakage Analysis and Minimisation

Leakage in WDN is an issue of great concern to municipalities and water utilities as it contributes to the exhaustion of their water resource (Araujo et al., 2006). Therefore, it is imperative that leaks are continuously detected and localised (Adedeji et al., 2017a) for speedy interventions. Various models are developed in the literature to estimate the leakages in the network (Araujo et al., 2006; Dai & Li, 2014; Giustolisi et al., 2008). From the results of the models, ANNs are trained to estimate the leakage in the water distribution system (Jang et al., 2018). The strategies are based on single and multi-layer feed-forward ANNs. The ANN estimated leakage is compared to principal component analysis with a multi-layer scheme providing better accuracy. Furthermore, Makaya & Hensel (2015) developed a leakage detection technique based on ANN forecasted flow dynamics.

2.4.3 ANN in water quality assessment

Water quality is one of the most important aspects involved in water network management. It is required by regulations that water delivered to the consumers must meet certain quality requirements to ensure that their health is not compromised. In the work of Adedaja et al. (2018), various water quality models are interrogated extensively. The advantages and disadvantages are presented, and the suggestion is made to embed hydraulic analysis in the water quality model, and in the identification of contamination sources. In Cordoba et al. (2014), historic parameters known to influence the quality of water are used to train the ANN model. The developed model as shown in Figure 2.5 is used to estimate the quality of water. A similar approach, with a difference being the input parameters was adopted in (Singh et al., 2009). The dissolved oxygen was computed together with the biochemical oxygen demand as the measure of the water quality (Singh et al., 2009).

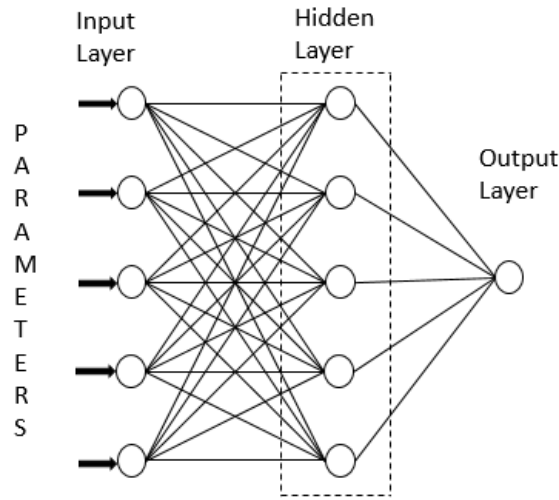


Figure 2.5: ANN structure for water quality assessment (Cordoba et al., 2014)

In (Chebud et al., 2012), data obtained from remotely located sensors is fed to a previously defined ANN model to estimate the water quality.

2.4.4 ANN in Demand Forecasting

Demand forecasting in WDN ensures that the network is optimally operated to meet user requirements. As the demand is time-varying and stochastic, the prediction of its uncertainty becomes an important aspect of network operation. Various methodologies for time-series data modelling were compared in (Anele et al., 2017) and a model conditional processor was adopted in (Anele et al., 2018). The efficiency of ANNs has made conventional regression and time-series methods obsolete, and it has progressed knowledge-based prediction schemes in water-demand forecasting (Liu et al., 2003; Msiza et al., 2008). In (Adamowski et al., 2012) the conventional methods are compared to ANNs and wavelet artificial neural networks (WA-ANN). Ghiassi et al. (2008) used a dynamic artificial neural networks (DANN) model with 99 % accuracy with monthly, weekly and daily data. Thus ANNs have been used for short-term water demand forecast (Jain et al., 2001), peak daily water demand forecast (Adamowski, 2008) amongst

other applications, due to their efficiency compared to regression models.

2.5 Summary

Efficient pressure control in a water distribution network is essential to improve its performance. The effective implementation of pressure control could see improvement of the sustainability of WDNs. This chapter investigates the pressure control solution methods that are often applied in WDNs. Methods commonly employed in the literature may be categorized as: (1) classical control, (2) advanced control, (3) optimal control, (4) real-time control, and (5) model-free control. It is evident from the literature that several methods have been put forward to control the pressure in WDNs adequately. However, shortcomings exist in the proposed methodologies. In the classical control case, the first deficiency is its inability to manipulate multiple variables at the same time, and the second concerns the fluctuations in pressure observed by researchers. The complexity of computations that must be solved in advanced and optimal control methods are major concerns raised in the literature. However, they do eliminate the issue of multiple manipulations of variables. In real-time control, classical PID controllers are augmented and deployed. As a result, the deficiency of multi-variable manipulation remains. Model-free control proposed in the literature relies only on the prior knowledge of the WDN. These methods are rigid and cannot be used should the topology of the network change. Furthermore, it is not clear whether these schemes could still yield a favourable outcome should they be tested under uncertain conditions. Owing to the shortcomings identified, it is clear that more work has to be done to reach harmonised solutions.

CHAPTER 3. MODELLING AND MATHEMATICAL FORMULATIONS

3.1 Introduction

A fundamental problem in operation of water distribution network is pressure management. This includes the controlling of the pressure to ensure that the water is supplied at the correct rate and that the pressure is minimised as the demand is lowered. The formulation of this control problem centres around the answers to some fundamental questions that must be addressed by the operators, and they can be summarised as:

- How is the pressure affected by the demand?
- How will excessive pressure affect the operation of the network?

To address these questions, some mathematical background is given in this chapter. The formulations presented in this chapter will form the basis for the subsequent chapters.

3.2 Water Distribution Network Modelling

A water distribution network (WDN) consists of links (pipes) and nodes (demand and source). Generally, the topology of a WDN permits utilisation of the graph-theoretic approach to define its model. Consider a WDN that consists of a N_b number of links or

pipes, N_n number of nodes encompassing n_s number of sources nodes, and n_d number of demand nodes. The nodal balance equation can be expressed as

$$C_{ij}Q = I \quad (3.1)$$

where, $I \in \forall N_n$ is a vector of nodal injections and demands and $Q \in \forall N_b$ is a vector of flows in the pipes. C_{ij} is $N_n \times N_b$ node-branch incidence matrix. Matrix C_{ij} can be described as

$$C_{ij} = \begin{cases} +1, & \text{if flow in branch } j \text{ leaves node } i \\ -1, & \text{if flow in branch } j \text{ enters node } i \\ 0, & \text{if branch } j \text{ is not incident to node } i \end{cases} \quad (3.2)$$

and decomposed as

$$C_{ij} = \begin{bmatrix} C_s \\ C_l \end{bmatrix} \quad (3.3)$$

For demand nodes, the nodal balance equation takes the form

$$C_l Q = -L \quad (3.4)$$

In Equation 3.3, C_s and C_l are the node-branch incidence matrices for the source and load nodes respectively while L is the demand vector of the load nodes in Equation 3.4. The topological matrices defining the energy conservation of the pipes for a closed-loop water distribution network can be expressed as

$$\Delta h = \begin{bmatrix} C_s^T & C_l^T \end{bmatrix} \begin{bmatrix} h_s \\ h_l \end{bmatrix} \quad (3.5)$$

where, h_s and h_l are vectors of pressures at sources and load nodes, respectively. For each pipe i , the pressure drop has a general form that is given in (3.6)

$$\Delta h = k_p Q_i^\alpha = k_p Q_i |Q_i|^{\alpha-1} \quad (3.6)$$

where k_p is the pipe resistance and α is the pressure exponent. It is important to note that for pipes with PRVs installed, the total pressure (head) loss will encapsulate the minor loss m due to the valve [Rossman et al. \(2000\)](#). Rearranging equation 3.5 and substituting (3.6) in (3.5) yields

$$k_p |Q|^{\alpha-1} Q - C_s^T h_s - C_l^T h_l = 0 \quad (3.7)$$

Defining matrix A as $A = \text{diag}(k_p |Q|^{\alpha-1})$, then

$$AQ - C_s^T h_s - C_l^T h_l = 0 \quad (3.8)$$

Equations 3.4 and 3.8 are the hydraulic equations that define the operation of the WDN. Their Newton's solution yields the hydrostatic pressure h and the water flows through the pipes Q .

3.2.1 Solution of the WDN problem

Given the sets of nodal withdrawals and fixed head pressure at the supply nodes, the solution of the WDN entails finding a set of flows Q and pressure h at load nodes. In this work, the content model is used.

3.2.1.1 Hydraulic Simulation by Newton Solution of the Content Model

To describe the Content Model, the formulation is written as

$$\text{Minimise } F(Q) \tag{3.9}$$

subject to

$$C_l Q + L = 0 \tag{3.10}$$

The Kuhn-Tucker condition gives

$$\nabla F(Q) + C_l^t \Lambda = 0 \tag{3.11}$$

and

$$C_l Q + L = 0 \tag{3.12}$$

The first order approximation of (3.11) and (3.12) gives

$$\nabla F(Q^r) + C_l^t \Lambda^r + \nabla^2 F(Q^r) \Delta Q + C_l^t \Delta \Lambda = 0 \tag{3.13}$$

and

$$C_l \Delta Q = 0 \tag{3.14}$$

The development of (3.13) and (3.14) gives

$$\Lambda^{r+1} = - [C_l H^{-1} C_l^t]^{-1} C_l H^{-1} g \tag{3.15}$$

and

$$Q^{r+1} = Q^r - H^{-1} g + H^{-1} C_l^t [C_l H^{-1} C_l^t]^{-1} C_l H^{-1} g \tag{3.16}$$

In Equations 3.15 and 3.16, $\Lambda = h_l$, $g = \nabla F(Q)$ and $H = \nabla^2 F(Q) = \text{diag}\{\alpha k Q^{\alpha-1}\}$.

In general, Equation 3.6 is applicable for simulation of the WDNs without any devices installed on the pipes. For the simulation of the presence of the PRVs, Equation 3.17 takes the form,

$$\Delta h = kQ^\alpha + mQ^2 \quad (3.17)$$

where, m = minor loss coefficient of the valve (Rossman et al., 2000; Todini, 2008). It can be noted that a non-linear term is now added to the steady-state model of the WDNs and this may pose additional numerical complexities in the hydraulic simulation (Todini, 2008).

3.3 Pressure Control in Water Distribution Networks

3.3.1 Classical Model-Based Pressure Control Problem Formulation

The objective of the scheme is to ensure that the pressure in the system is considerably reduced. Furthermore, the problem is formulated to keep the pressure at all nodes above the minimum and below the maximum. Mathematically, the objective can be expressed as (Nicolini, 2011)

$$\min f = \omega_i \sum (h_i(t)^{ref} - h_i(t)^{calc})^2 \quad (3.18)$$

where ω is the weighting factor. The objective is subject to the following constraints.

- The continuity equation at each node. expressed as

$$C_i Q + L = 0 \quad (3.19)$$

- The head pressure loss constraint (conservation of energy) of each pipe.

$$\Delta h - C_s^T h_s - C_l^T h_l = 0 \quad (3.20)$$

- Nodal head constraint

$$h_i(t) \geq h_i(t)^{min} \quad (3.21)$$

$$h_i(t) \leq h_i(t)^{max} \quad (3.22)$$

- Pipe flow constraint

$$Q_i \text{ unrestricted} \quad (3.23)$$

- Valve opening

$$0 < u_{ij} \leq 1 \quad (3.24)$$

In (3.24), $u \in \{0 : 1\}$ is a diameter multiplier (control input to the PVRs) which imitates the presence of a valve (Nicolini, 2011). The choice of $h_i(t)^{ref}$ and $h_i(t)^{min}$ is of great importance because the demand varies with time. Ordinarily, at lower demands, the pressure in the network would generally be in excess of what is required and at higher demands, the pressure falls below the required (Puust et al., 2010). Therefore, $h_i(t)^{ref}$ and $h_i(t)^{min}$ should be adapted accordingly as the demand varies. The flow through the pipes is left unrestricted as ordinarily, the change in the valves will affect the flows in the whole system.

3.3.2 The Proposed Model-Free Pressure Control

Model-free control (MFC) with a reinforcement learning (RL) controller is used to learn the behaviour of WDNs (the environment) and, based on a given demand (state s), it determines the optimal adjustment of the PRVs (action a). RL is a subset of machine learning but unlike supervised (mapping input with outputs) and unsupervised (classification) learning, it learns directly from data in a dynamic environment. As such, RL does not need any prior information about the structure of the model. The works of Hamam & Hindi (1992) and Rao & Salomons (2007) indicate that one of the major challenges with supervised learning is that several thousands of simulations have to be performed in order to generate the dataset that can be used for training. An RL agent only needs the structure of the observation and the manipulated variables. The agent then determines the optimal policy $\pi^*(s)$ to decide on what actions to take given a state of the environment. For each action proposed by the agent, it is rewarded and the policy is updated based on the reward. The structure of an RL agent is shown in Figure 3.1.

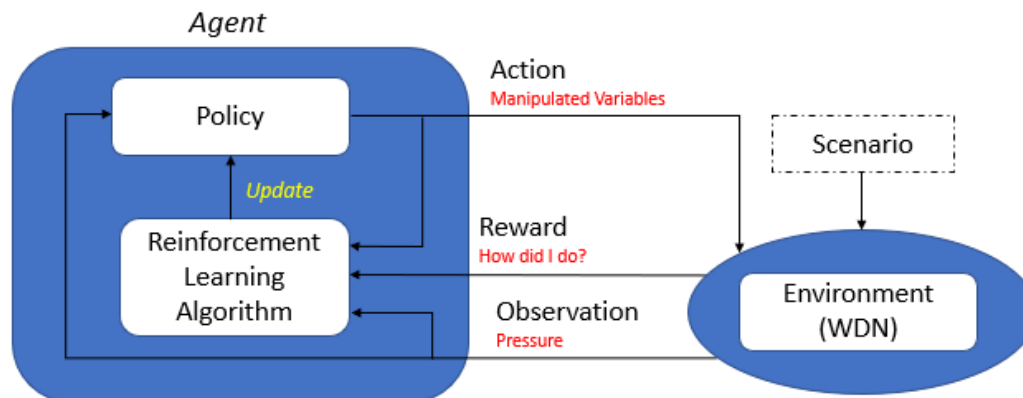


Figure 3.1: Reinforcement Learning Agent

Given a scenario or state s and an action a , the environment produces the observation and rewards the agent for the proposed action. Equation 3.25 shows the reward function that is used. It can be seen that the reward is either 100 or -10. The RL agent is rewarded

with 100 if the absolute value of the difference of $h - h_{ref}$ is less than the threshold or is positive and less than the threshold, otherwise the agent is rewarded with -10.

$$r = \begin{cases} 100, & \text{if } |h - h_{ref}| < \textit{threshold} \textbf{ or } h - h_{ref} > 0 \textbf{ and } < \textit{threshold} \\ -10, & \textit{otherwise} \end{cases} \quad (3.25)$$

The algorithm is then invoked and upon convergence, the policy is updated. In this work, the value iteration algorithm is used to update the policy. The pseudocode for the algorithm is shown in Algorithm 2.

Algorithm 2: Value Iteration Algorithm

```

1 Initialisation;
2  $V(s) \leftarrow 0$ ;
3  $v \leftarrow 0$ ;
4 Convergence  $\leftarrow$  false;
5 while !Convergence do
6      $\Delta \leftarrow 0$ ;
7     for  $s \in S$  do
8          $v \leftarrow V(s)$ ;
9          $V(s) \leftarrow \max_a \sum_{s',r} p(s', r|s, a)[r + \gamma V(s')]$ ;
10         $\Delta \leftarrow \max(\Delta, |v - V(s)|)$ ;
11        if  $\Delta < \textit{err}$  then
12            Convergence  $\leftarrow$  true
13 Policy  $\pi$ ;
14  $\pi(s) \leftarrow \arg \max_a \sum_{s',r} p(s', r|s, a)[r + \gamma V(s')]$ ;
15 Nomenclature;
16  $V(s) \leftarrow$  Value function;
17  $v \leftarrow$  Previous value of the function;
18  $s \in S \leftarrow$  Scenario in Figure 3.1 ;
19  $p \leftarrow$  State transition function;
20  $a \leftarrow$  Action (Control settings);
21  $r \leftarrow$  Reward;
22  $\gamma \leftarrow$  Discount factor;

```

For every scenario $s \in S$ observed by the environment in Figure 3.1, p , pressure from a critical node (CN) is obtained and fed to the RL agent. It has been shown in the

literature that the pressure in WDNs can be controlled, based on the pressure observed at a critical node (Berardi et al., 2015; Page et al., 2017c). A critical node is defined as a sensitive node with lowest pressure. Actions (a) are proposed by the RL agent (using the current policy) based on the observed pressure and manipulated variables in the environment are updated. For every action (a) and state s , $p: a \times s \rightarrow r$, obtains the reward r . As the reward function is based purely on the pressure at a critical node (h_{CN}), $p: a \times s \rightarrow r$ relies on the invocation of Equation 3.26 (interaction with the environment in Figure 3.1) for computing h_{CN} . This operation on Line 8 of algorithm 2 updates the value function $V(s)$ and compare it to the previous v given by $a \leftarrow a - 1$ to compute. This operation is repeated for $s \rightarrow s + 1$ to determine appropriate action for the current demand. The environment in this work is simulated by a quadratic approximation of a WDN’s hydraulic operation. Ordinarily, the environment would be the solution of the WDN’s model as defined by Equations 3.4 and 3.8. The solution is often computed using the open source EPANET software (Rossman et al., 2000). However, in this work, a MATLAB script was written to obtain the solution of the WDN. For a daily demand variation in (Jowitt & Xu, 1990), the pressure at a critical node (h_{CN}) is recorded with the corresponding vector of control inputs computed as shown in Section 3.3.1. The quadratic function is chosen for emulation due to the nature of the flow-pressure relationship shown in (3.6). Equation 3.26 presents the quadratic formulation for the approximation of the hydraulic operation of WDN.

$$\begin{aligned}
h_{CN} = & \begin{bmatrix} u_1 & \dots & u_n & L_1 & \dots & L_m \end{bmatrix} \begin{bmatrix} a_{11} & \dots & a_{1n} & a_{1(n+1)} & \dots & a_{1(m+n)} \\ \vdots & \dots & \dots & \dots & \dots & \vdots \\ a_{n1} & \dots & \dots & \dots & \dots & a_{n(m+n)} \\ a_{(n+1)1} & \dots & \dots & \dots & \dots & a_{(n+1)(m+n)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{(m+n)1} & \dots & a_{(m+n)n} & a_{(m+n)(n+1)} & \dots & a_{(m+n)(m+n)} \end{bmatrix} \begin{bmatrix} u_1 \\ \vdots \\ u_n \\ L_1 \\ \vdots \\ L_m \end{bmatrix} \\
& + \begin{bmatrix} b_1 & \dots & b_n & b_{n+1} & \dots & b_{m+n} \end{bmatrix} \begin{bmatrix} u_1 \\ \vdots \\ u_n \\ L_1 \\ \vdots \\ L_m \end{bmatrix} + c
\end{aligned} \tag{3.26}$$

In (3.26), the vector $\mathbf{U} = [u_1 \dots u_n]$ represents the control inputs to the PRVs and n is the number of the installed PRVs. $\mathbf{L} = [L_1 \dots L_m]$ is the vector of nodal withdrawal at the demand nodes and scalar h_{CN} is the pressure at the critical node. The unknown coefficients of the quadratic formula are $a_1 \dots a_{m+n}$ and $b_1 \dots b_{m+n}$ while the constant term is c . If a symmetric matrix

$$\mathbf{M} = \begin{bmatrix} a_{11} & \dots & a_{1n} & a_{1(n+1)} & \dots & a_{1(m+n)} \\ \vdots & \dots & \dots & \dots & \dots & \vdots \\ a_{n1} & \dots & \dots & \dots & \dots & a_{n(m+n)} \\ a_{(n+1)1} & \dots & \dots & \dots & \dots & a_{(n+1)(m+n)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{(m+n)1} & \dots & a_{(m+n)n} & a_{(m+n)(n+1)} & \dots & a_{(m+n)(m+n)} \end{bmatrix} \tag{3.27}$$

and matrix

$$\mathbf{B} = \begin{bmatrix} b_1 & \dots & b_n & b_{n+1} & \dots & b_{m+n} \end{bmatrix} \quad (3.28)$$

are partitioned to have the unknown coefficients as sub-matrices of \mathbf{M} and \mathbf{B} , Equation 3.26 may expressed in simple form as

$$h_{CN} = \begin{bmatrix} \mathbf{U} & \mathbf{L} \end{bmatrix} \begin{bmatrix} \Lambda_1 & \Lambda_2 \\ \Lambda_2^T & \Lambda_4 \end{bmatrix} \begin{bmatrix} \mathbf{U}^T \\ \mathbf{L}^T \end{bmatrix} + \begin{bmatrix} \Lambda_5 & \Lambda_6 \end{bmatrix} \begin{bmatrix} \mathbf{U}^T \\ \mathbf{L}^T \end{bmatrix} + c \quad (3.29)$$

where Λ_1 and Λ_2 have the dimension $n \times n$ and $n \times m$ respectively while Λ_4 has the dimensions $m \times m$. Λ_5 and Λ_6 are vectors with dimensions $1 \times n$ and $1 \times m$ respectively. The results of the matrix operation in Equation (3.29) can be expressed in a compact form as

$$h_{CN} \approx A_B \delta \quad (3.30)$$

where the matrix of unknown coefficients is denoted by δ and a matrix composed of vectors of known demand, control inputs and constants is assigned the symbol A_B . To determine the unknown coefficients, the least square solution expressed as

$$\delta = [A_B^T A_B]^{-1} A_B^T h_{CN} \quad (3.31)$$

is used while the MATLAB's backslash operation solved Equation (3.31).

3.4 Summary

The mathematical background described in this chapter provides the framework for this study. The model is formulated based on the graph-theoretic principles. The expression for the pressure-controlling devices is also given. The solution of the model, based on the Newton solution of the content model, is presented in this chapter. The pressure control

formulations are divided into two broad categories: (1) classical model-based control and (2) proposed model-free control. Optimisation-based pressure control is used as a classical model-based strategy and the formulation is presented. The proposed model-free control scheme based on Reinforcement Learning is presented. The operation of the proposed model is explained in detail and the pseudo-code algorithm used by the RL agent is given. The environment in the RL agent is simulated by the quadratic approximation of the water distribution network. The formulation of the quadratic approximation is given, and the solution steps are also given.

CHAPTER 4. IDENTIFICATION OF CRITICAL NODES

4.1 Introduction

Due to budgetary and physical constraints, there is a need to estimate the system pressure from limited nodal measurements. In WDNs, critical nodes are used as indicators for the state of operation of the network. These are sensitive and are susceptible to the occurrence of over- and under-pressures as the nodal withdrawal varies. It is well known that the variation of the demand on the network influences the pressure in the WDNs. The sensitivity of a node i can be determined using Equation 4.1.

$$S_i(t) = \frac{\partial h_i}{\partial L_i} \quad (4.1)$$

and

$$\frac{\partial h_i}{\partial L_i}(t) \approx \frac{h_i - h_{ref,i}}{\Delta L_i} \quad (4.2)$$

where,

$$\Delta L = L_{base} - L_{current} \quad (4.3)$$

L_{base} is the base demand to the network and $L_{current}$ is the current demand. A vector can now be defined with the ranking of the nodes with the highest variation as

$$\mathbf{S} = \begin{bmatrix} S_1(t) & S_2(t) & \dots & S_n(t) \end{bmatrix} \quad (4.4)$$

where S_1 is the node with the highest variation and S_n has the lowest variation. A threshold of the variation could be denoted by Θ . Therefore, nodes that have variation that is less than the threshold could be eliminated from Equation 4.4, with the proviso that the number of critical nodes must be limited to a fixed number z and the resultant be denoted by $\bar{\mathbf{S}}$. For a demand pattern over a time period (m periods), the critical node index vector could be defined. A matrix with dimension $m \times z$ comprising critical nodes could be defined as

$$CNI = \begin{bmatrix} S_1(t) & S_2(t) & \dots & S_z(t) \\ S_1(t+1) & S_2(t+1) & \dots & S_z(t+1) \\ \vdots & \vdots & \vdots & \vdots \\ S_1(t+m) & S_2(t+m) & \dots & S_z(t+m) \end{bmatrix}, \forall S > \Theta \in \bar{\mathbf{S}} \quad (4.5)$$

The final ranking can be defined as a vector with a node having the highest variation and appearing in most rows as the most critical (first element in the vector). The reverse will be the least critical node and last in the vector. The solution to the identification of critical nodes can be determined using the algorithm and its structure is shown in Algorithm 3.

Algorithm 3: Greedy Algorithm for Identification of Critical Nodes

Input: Network Parameters

Input: Define base demand over a period

Result: Critical Node

```
1 Initialization;
2  $CNI \leftarrow 0$ ;
3 Convergence  $\leftarrow$  False;
4 while !True do
5     Run hydraulic simulation (Section 3.2.1);
6      $\mathbf{S}_i = \begin{bmatrix} S_1 & S_2 & \dots & S_n \end{bmatrix}$ ;
7     do if Length of  $\mathbf{S}_i > z$  then
8          $\bar{\mathbf{S}}_i \leftarrow \mathbf{S}_i(\text{rows} = 1; \text{column} = 1 \text{ until } z)$  ;
9     else
10         $\bar{\mathbf{S}}_i \leftarrow \mathbf{S}_i$ 
11     $CNI(\text{row} = i, \text{column} = \text{all}) \leftarrow \bar{\mathbf{S}}_i$ ;
12    if at the end of period then
13        Convergence  $\leftarrow$  True
14 Reshape  $CNI$  to be vector  $\bar{\mathbf{CNI}}$ ,  $\bar{\mathbf{CNI}}_1$ , node with highest variation ;
15 return  $\bar{\mathbf{CNI}}_1$ ;
```

4.2 Numerical Experiment 1

The test case shown in Figure 4.1 consists of 70 nodes and 108 pipes. Nodes (1, 69, 70) are the supply nodes. Parameters of the nodes and pipes are given in Table C.4 and Table C.3 as previously used in the work of Adedeji in Adedeji et al. (2018b). The demand pattern used is shown in Figure 4.2.

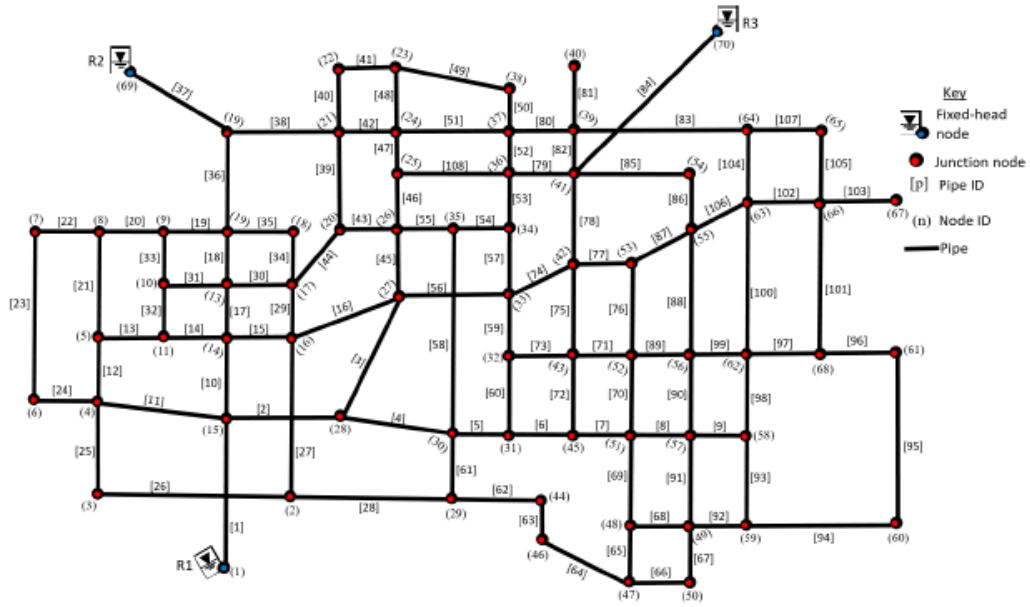


Figure 4.1: Case Study 1.

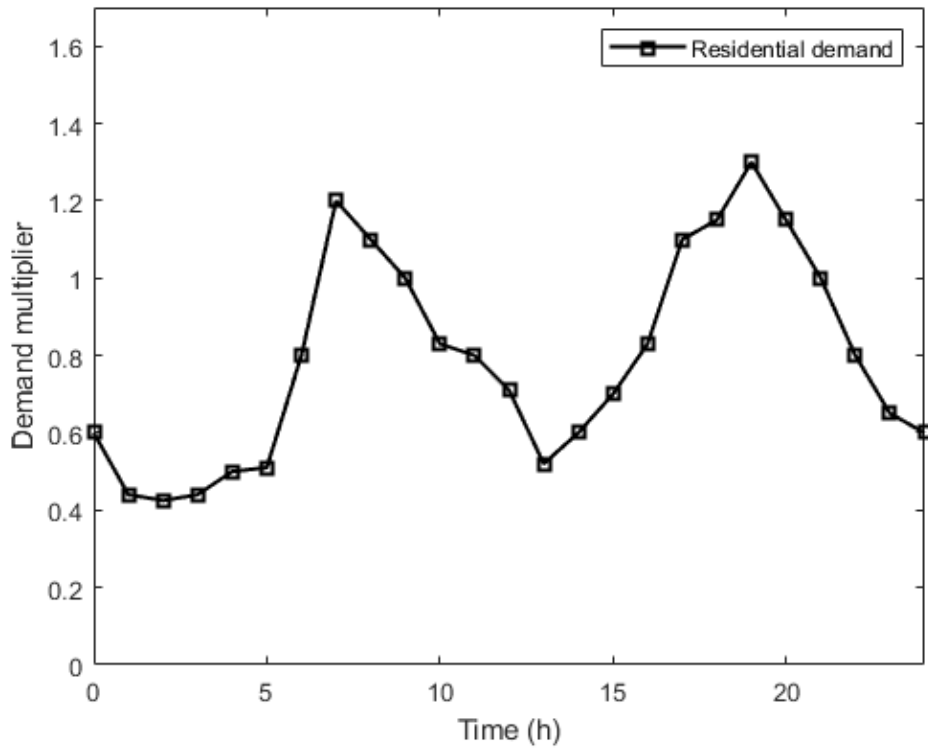
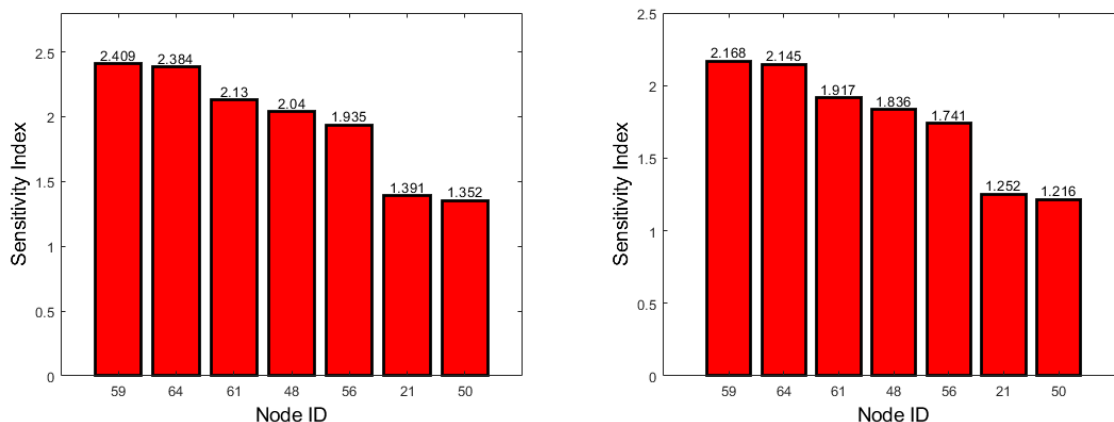


Figure 4.2: The demand pattern.

The results of the implementation of Algorithm 3 are depicted in figures 4.3a and 4.3b. The number of critical nodes is restricted to 7. It can be seen that for both the maximum and minimum demands, some nodes (59, 64, 61, 48, 56, 21 and 50) are critical. Furthermore, it is evident that node 66 is the most critical node throughout the testing set. It can be seen that the highest sensitivity index is found at maximum demand. This is as a result of more dip in the nodal pressure as the demands hits the maximum.



(a) Nodal head variation at maximum demand. (b) Nodal head variation at minimum demand.

Figure 4.3: Nodal head variations for Case Study 1.

4.3 Numerical Experiment 2

The test case Figure 4.4 consists of 300 nodes and 447 pipes. Of the 300 nodes, 3 are configured as fixed head nodes (supply nodes). Two PRVs are installed on pipes 242 and 415. Parameters of the nodes and pipes are given in Table C.5 and Table C.6 as previously used in the work of Adedeji in Adedeji et al. (2018b) and Adedoja et al. in Adedoja et al. (2020).

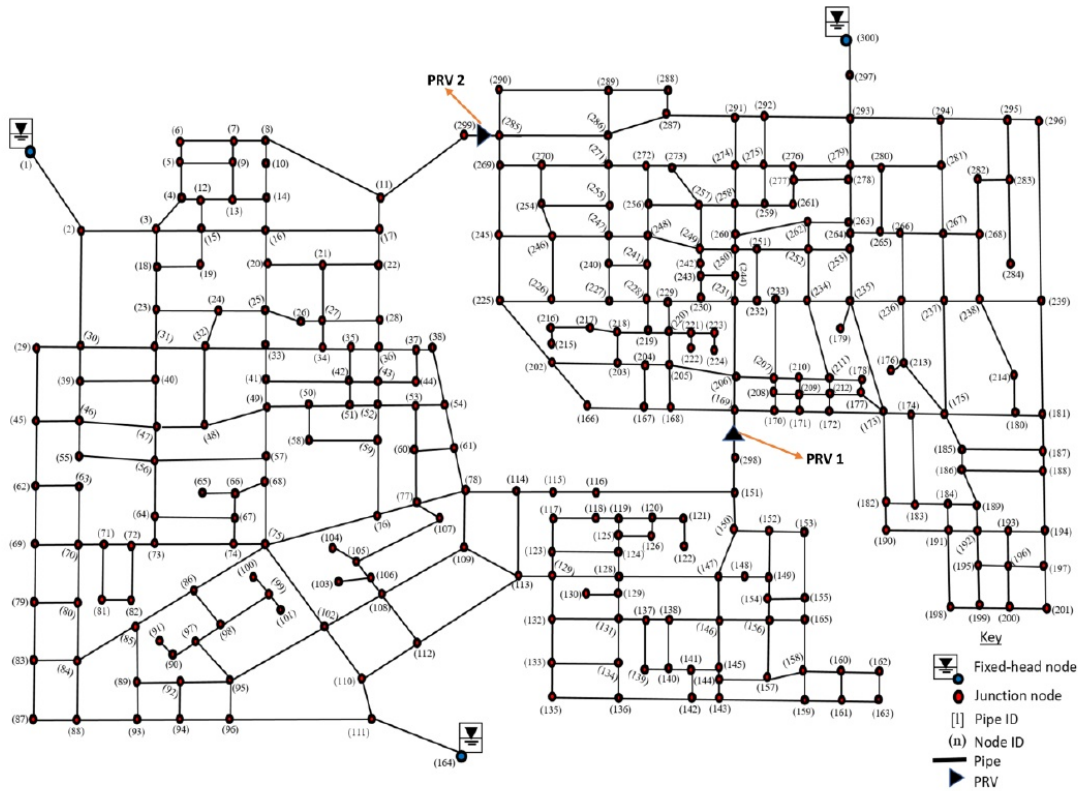
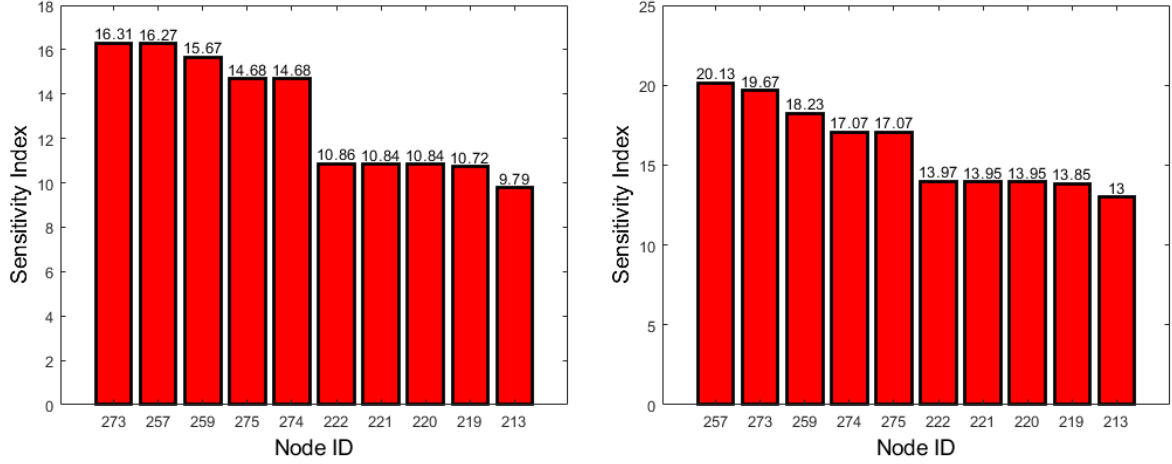


Figure 4.4: Case Study 2.

The number of critical nodes for the case study in Figure 4.4 were restricted to 10 nodes. The implementation of Algorithm 4 for the demand pattern shown in Figure 4.2. Evidently, the set of nodes consisting of 273, 257, 259, 275, 274, 222, 221, 220, 219 and 213 for maximum demand is critical whereas 257, 273, 259, 274, 275, 222, 221, 220, 219 and 213 is critical at minimum demands. The results obtained for this case study, as shown in Figures 4.5a and 4.5b respectively, show that the proposed scheme identified the same sets of nodes for the maximum and minimum, however, the order of the sensitivity of the nodes varied. This shows that the proposed greedy algorithm is unbiased.



(a) Nodal head variation at maximum demand. (b) Nodal head variation at maximum demand.

Figure 4.5: Nodal head variations for Case Study 2.

4.4 Summary

The greedy algorithm proposed for identification of critical nodes is applied in two case studies in this chapter. First, the mathematical formulation around the algorithm is given as a background. On application of the algorithm, 7 and 10 nodes were fixed for numerical experiments 1 and 2. Consistent results were obtained for both experiments. Some nodes were found to be critical for maximum and minimum demand. It was also found that for maximum demand the variation is higher, in both experiments.

CHAPTER 5. MODEL-FREE PRESSURE CONTROL

5.1 Introduction

In this chapter, the appropriateness of the scheme put forward in Chapter 3 is tested. Three test cases of WDNs are used to evaluate the effectiveness of the proposed model-free control scheme. All case studies have been used previously in the literature ([Ozger & Mays, 2003](#); [Adedeji et al., 2018b](#); [Adedeji, 2020](#)) and MATLAB software was used for all simulations.

5.2 Numerical Experiment 1

The first case study is shown in Figure 5.1, and consists of 21 pipes and 15 nodes, with 2 of them being source nodes. Five pressure-reducing valves (PRVs) were installed in the network. Pipes 1, 9, 10, 17, and 21 were selected as the installation location for the PRVs. Parameters of the nodes and pipes are given in Tables C.1 and C.2.

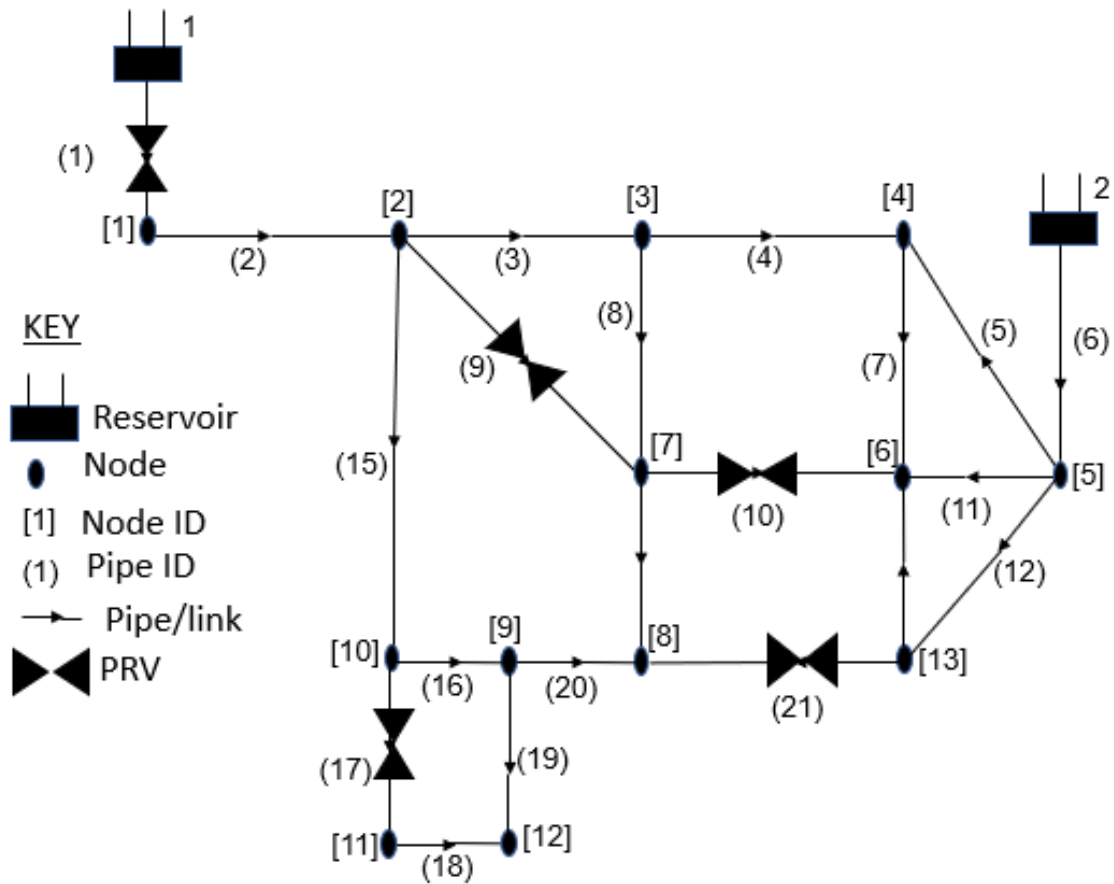


Figure 5.1: Schematic diagram for Case Study 1.

In Figures 5.2 and 5.3, the impact of pressure control on the operation of the WDN is depicted. It is evident in Figure 5.2 that, the flow in some pipes decreased and in others increased as a result of pressure control. This is allowed by the unrestricted flow in the formulation of the control problem. Figure 5.3 shows an increase in pressure drop along the pipes for the demand in Table C.2 (demand factor of 100%), especially those pipes with PRVs installation. This is due to the losses introduced by the valves and their subsequent adjustment. It is evident that pipes with PRVs installed (1, 9, 10, 17, and 21) experienced a significant increase in pressure drop. This is due to a minor loss of the PRVs and losses as a result of their partial closure.

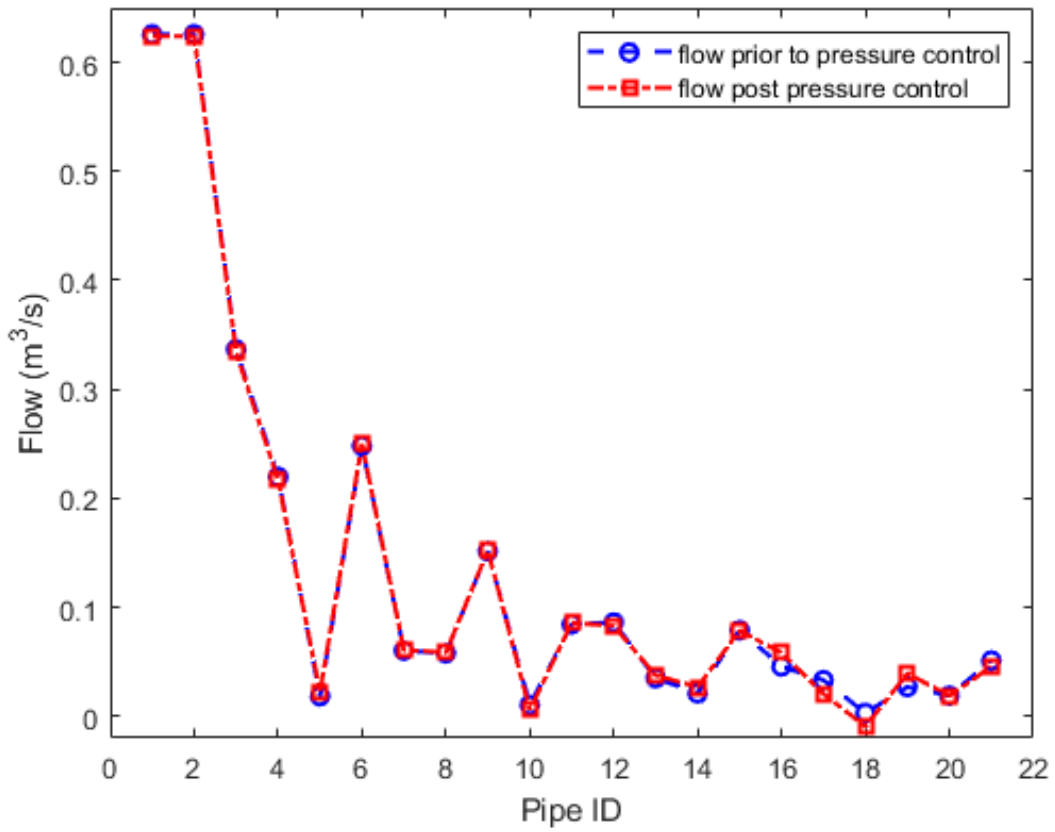


Figure 5.2: Pipe flows for Case Study 1.

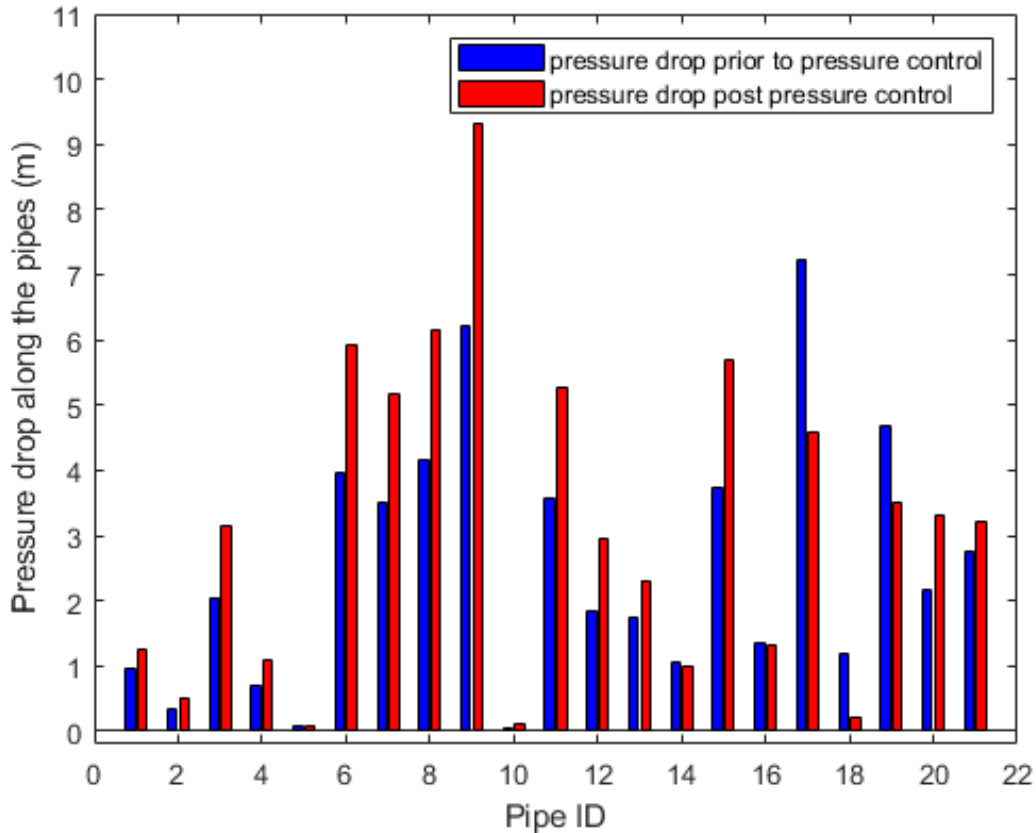


Figure 5.3: Nodal pressure heads for case study 1.

The head observed in the critical node (CN) of the first test case is presented in Table 5.1. The CN in Case Study 1 is marked as node 12 in Figure 5.1. In Table 5.1, the head prior to the implementation of any control scheme is presented with the observation from two of the control schemes in Sections 3.3.1 and 3.3.2. The optimal actions from the RL agent are tested on the model and the results are also presented in Table 5.1. Equation 3.4 is used to determine the effect of the pressure control on the nodal withdrawals. Evidently, both schemes significantly reduce the pressure observed at the critical node. However, the scheme in Section 3.3.1 requires an explicit model, whereas, the alternative scheme proposed could achieve good results without an explicit model. Furthermore, it can be seen that the control does not affect the amount of water withdrawn at the

demand nodes.

Table 5.1: Pressure observed on the critical node at 80%, 100% and 120% demand Case study 1.

Demand Factor	h_{CN} Prior Control	h_{CN} Post MBC	h_{CN} Post MFC	h_{CN} RL Output Tested on a Model	L Prior	L Post
80%	52.84 m	46.04 m	45.93 m	45.89 m	699 L/s	699 L/s
100%	48.69 m	44.16 m	43.71 m	44.19 m	874 L/s	874 L/s
120%	43.76 m	41.49 m	41.95 m	41.34 m	1048.8 L/s	1048.8 L/s

h_{CN} prior Control: Uncontrolled nodal pressure head. h_{CN} post MBC: Model based controlled (MBC) nodal pressure head. h_{CN} post MFC: Model-free controlled (MFC) nodal pressure head. h_{CN} RL output tested on a model: Testing the control settings from the RL agent on the model.

In comparison, the model-based optimal controller achieved 13%, 10% and 6% pressure reduction for 80%, 100% and 120% loading respectively. Evidently, the percentage of pressure reduction achieved is reduced as the demand increases. This is a result of the overall pressure decrease as the demand increases (Puust et al., 2010). The threshold in Equation (3.25) was set to 0.5 m. It can be seen in Table 5.1 that the RL agent MFC scheme results in hydrostatic pressure of the CN being within the 0.5 margin set out in the reward function. The PRVs settings obtained from the RL agent were tested in the model in Section 3.2. The results obtained via the CN showed a difference of at most 0.15 m as compared to those attained via the model-based optimisation problem.

5.3 Numerical Experiment 2

Figure 5.4 shows the adapted case study in Figure 4.1 to include seven PRVs which are installed in the nominated location (1, 3, 5, 20, 46, 99, 102) of the WDN. Parameters of pipes and nodes are given in Table C.3 and C.4.

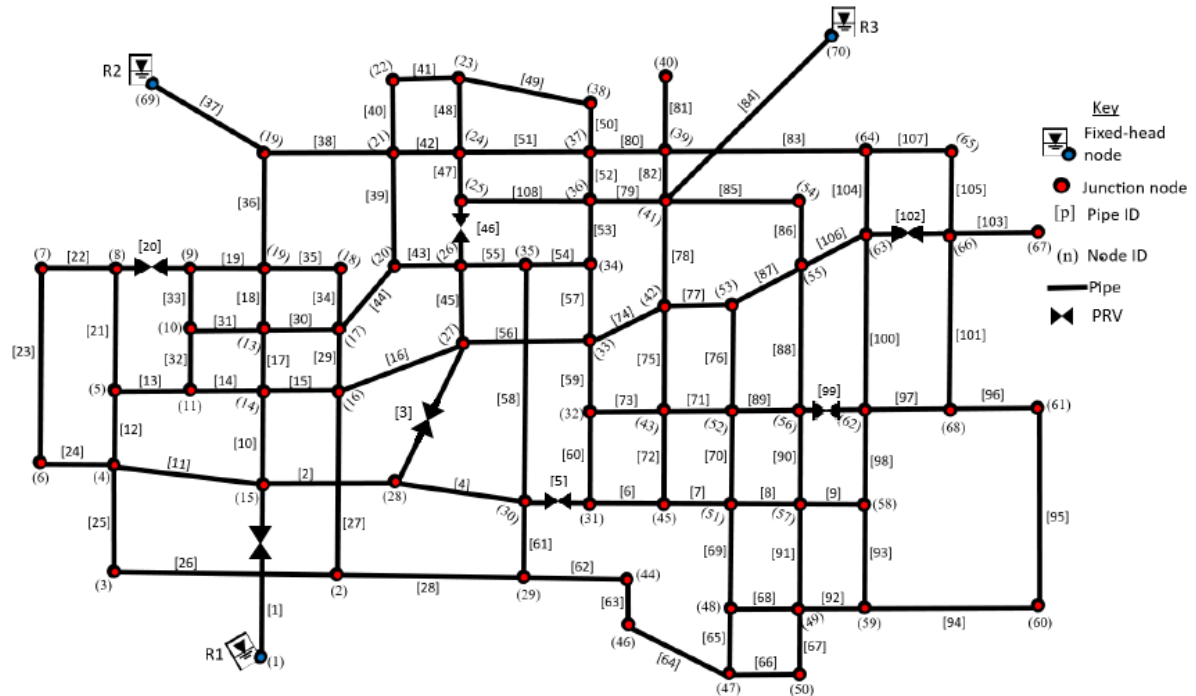


Figure 5.4: Case Study 2

In Figure 5.5 and Figure 5.6 it can be seen that the installation of PRVs and their subsequent adjustment results in decreased flows through the pipes, mainly, in the pipes with PRVs. Figure 5.6 shows consistency with Section 5.2. Pipes with PRVs installation show notably increased head drop which results in decreased pressure at the lower end of the pipe for the demand in Table C.4 (demand factor of 100 %). It can further be seen in Figure 5.6 that adjustment of head loss in some pipes affects the entire network.

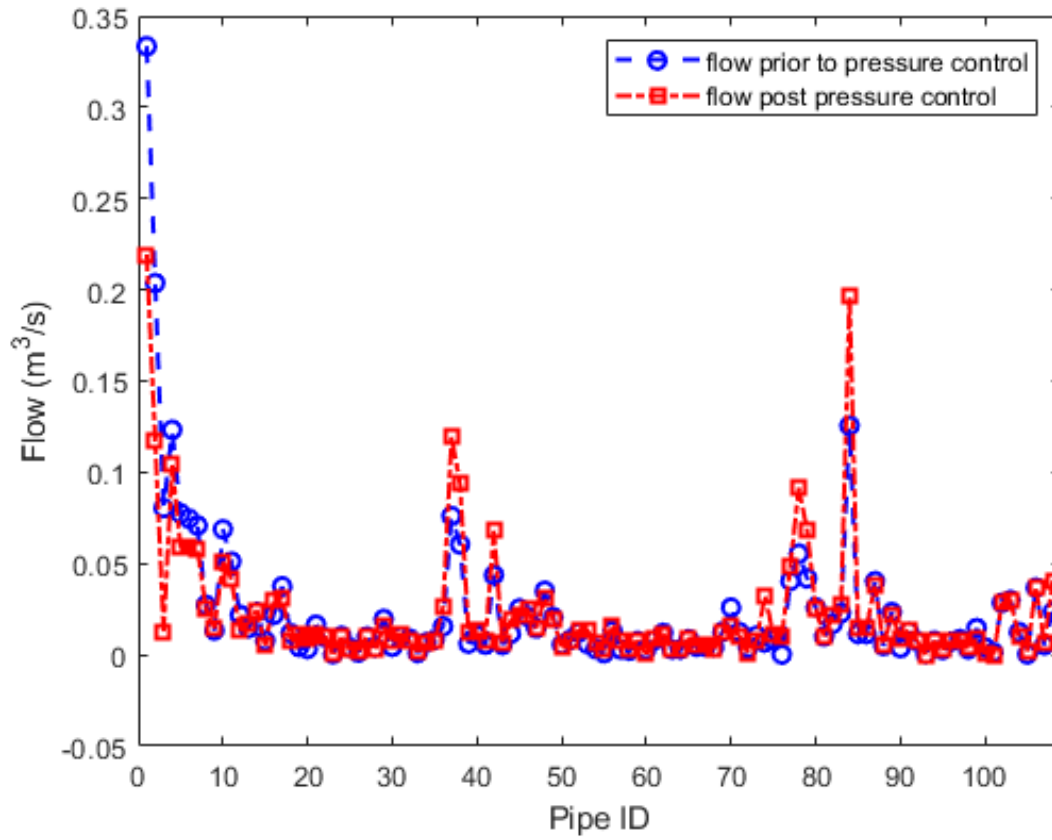


Figure 5.5: Pipe flows for Case Study 2

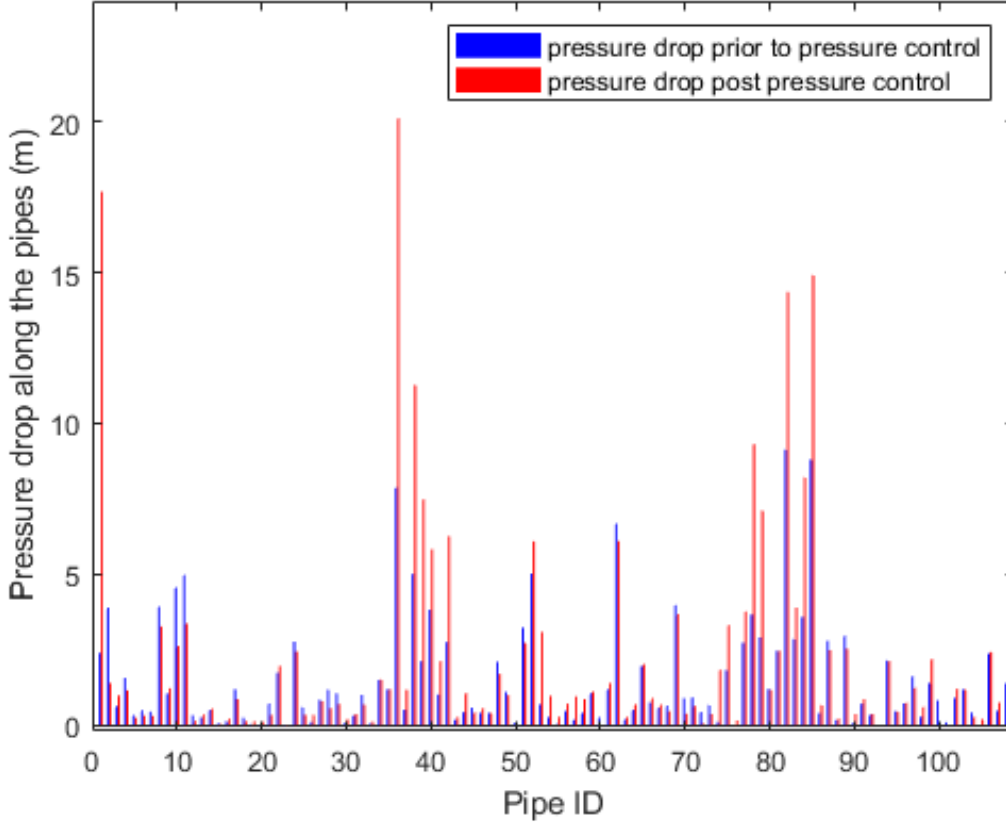


Figure 5.6: Nodal pressure heads for Case Study 2

To further establish the effectiveness of the proposed MFC, the RL agent was tested with three loading conditions for the network in Figure 4.1 and the results are presented in Table 5.2. The *threshold* in (3.25) was set to 0.5 m. Equation 3.4 is used to determine the effect of the pressure control on the nodal withdrawals. It can be seen from Table 5.2 that the proposed scheme is able to mimic the conventional optimisation procedures commonly employed. It is further evident that the actions/settings from the MFC yield valid results when tested on the model formulated. A noteworthy observation in Table 5.2 is that with all tested loading conditions, the MFC is able to achieve the solution without violating the *threshold* as tested on the WDN emulator and the model. In comparison, the MBC achieved 20.91 %, 15.47 % and 10.37 % for 80 %, 100 % and

120 % loading whereas the MFC achieved 20.67 %, 15.08 % and 10.52 %. Consistent with Table 2, the decrease in the nodal head on the CN was observed as the demand increases. The CN in Case Study 2 is marked as node 59 in Figure 5.1. It is worth noting that the proposed scheme does not rely on the model and therefore it can be deployed on real networks where modelling of the system could be a challenge. It can further be observed from Table 5.2 that the nodal withdrawal was not affected by the pressure control as the flows were increased in other pipes to ensure that the supply is satisfied. Furthermore, the computational simplicity of the proposed scheme adds to its strength.

Table 5.2: Pressure observed on the critical node at 80%, 100% and 120% demand Case study 2.

Demand Factor	h_{CN} Prior Control	h_{CN} Post MBC	h_{CN} Post MFC	h_{CN} RL Output Tested on a Model	$\sum L$ Prior	$\sum L$ Post
80%	79.47 m	62.85 m	63.04 m	62.57 m	428 L/s	428 L/s
100%	74.07 m	62.61 m	62.90 m	62.91 m	535 L/s	535 L/s
120%	67.67 m	60.65 m	60.55 m	60.49 m	642 L/s	642 L/s

h_{CN} prior Control: Uncontrolled nodal pressure head. h_{CN} post MBC: Model based controlled (MBC) nodal pressure head. h_{CN} post MFC: Model-free controlled (MFC) nodal pressure head. h_{CN} RL output tested on a model: Testing the control settings from the RL agent on the model.

5.4 Numerical Experiment 3

Two PRVs are installed in pipes 242 and 415 as shown in Figure 5.7. Parameters of the nodes and pipes are given in Table C.5 and Table C.6.

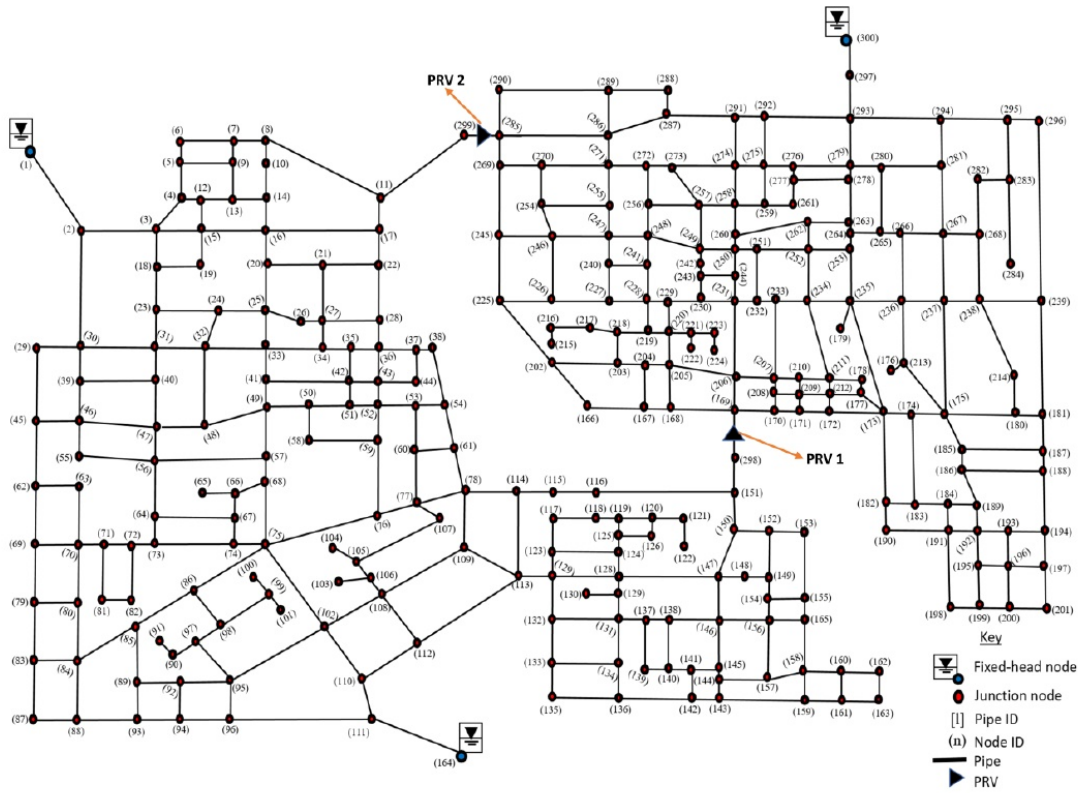


Figure 5.7: Case Study 3

In Figure 5.8 and Table 5.3 it can be seen that the installation of PRVs and their subsequent adjustment results in decreased flows through the pipes, mainly in the pipes with PRVs. Pipes with PRVs installed show noticeably increased head drop which results in decreased pressure at the lower end of the pipe, for the demands shown in Table C.5.

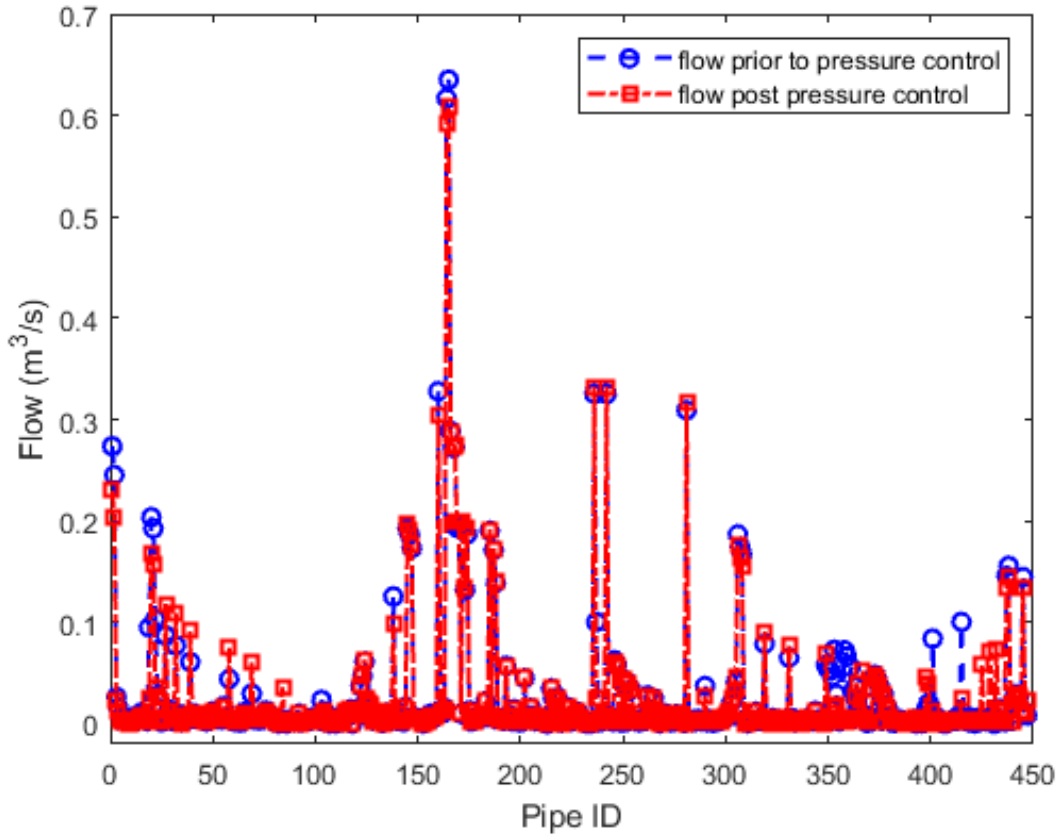


Figure 5.8: Pipe flows for case study3

Table 5.3: Flow through and Head across the PRVs.

PRV No.	Pipe ID	Pipe flow Without PRV L/s	Pipe flow With PRV L/s	Δh Without PRV	Δh With PRV
1	242	325.4	332.46	80.99 m	87.04
2	415	100.53 m	24.17	110.69 m	138.17

Δh : head loss

The proposed scheme in Section 3.3.2 is tested in this case and compared to the optimisation scheme put forward in Section 3.3.1. The *threshold* in (3.25) was set to 0.5 m. Equation 3.4 is used to determine the effect of the pressure control on the nodal

withdrawals. It can be seen from Table 5.4 that the proposed scheme is able to mimic the conventional optimisation procedures commonly employed. It is further evident that the actions/settings from the MFC yield valid results when tested on the model formulated. A noteworthy observation in Table 5.4 is that with all tested loading conditions, the MFC is able to achieve the solution without violating the *threshold* as tested on the WDN emulator and the model.

Table 5.4: Pressure observed on the critical node at 100% demand.

Demand Factor	h_{CN} Prior Control	h_{CN} Post MBC	h_{CN} Post MFC	h_{CN} RL Output Tested on a Model	$\sum L$ Prior	$\sum L$ Post
100%	27.28 m	18.23 m	17.99 m	17.87 m	913.5 L/s	913.5 L/s

h_{CN} prior Control: Uncontrolled nodal pressure head. h_{CN} post MBC: Model based controlled (MBC) nodal pressure head. h_{CN} post MFC: Model-free controlled (MFC) nodal pressure head. h_{CN} RL output tested on a model: Testing the control settings from the RL agent on the model.

5.5 Summary

The problem of pressure control in WDNs was investigated and presented in this chapter. The performance of the model-free control scheme was compared to the scheme commonly employed in the literature. It can be seen from the results that both schemes reduce the pressure in the WDN effectively. However, the strength of the proposed scheme lies in its ability to do so without any information about the model. This is significant because parameters of the pipes and/or PRVs are affected over time by environmental conditions, These changes make the model inaccurate, leading to useless results, unless the model is continuously updated with the values of estimated parameters. By contrast, in the proposed scheme the controller’s information is updated by the dynamics of the network in operation. Therefore, a RL based controller may be effective

in a case where the parameters of the existing infrastructure are hard to estimate. In addition to its ability to determine the settings of the manipulated variables without a model of the system, the strength of a RL based controller is its simpler computational process, compared to solving the optimisation problem in model based control.

CHAPTER 6. MULTI-PERIOD MODEL-FREE PRESSURE CONTROL

6.1 Introduction

In this chapter, the control scheme put forward in Section 3.3.1 is evaluated under multi-periods. A 24-hour demand factor is used to represent the multiple periods during which the scheme is tested. Figure 6.1 represents the demand factor over 24 hours.

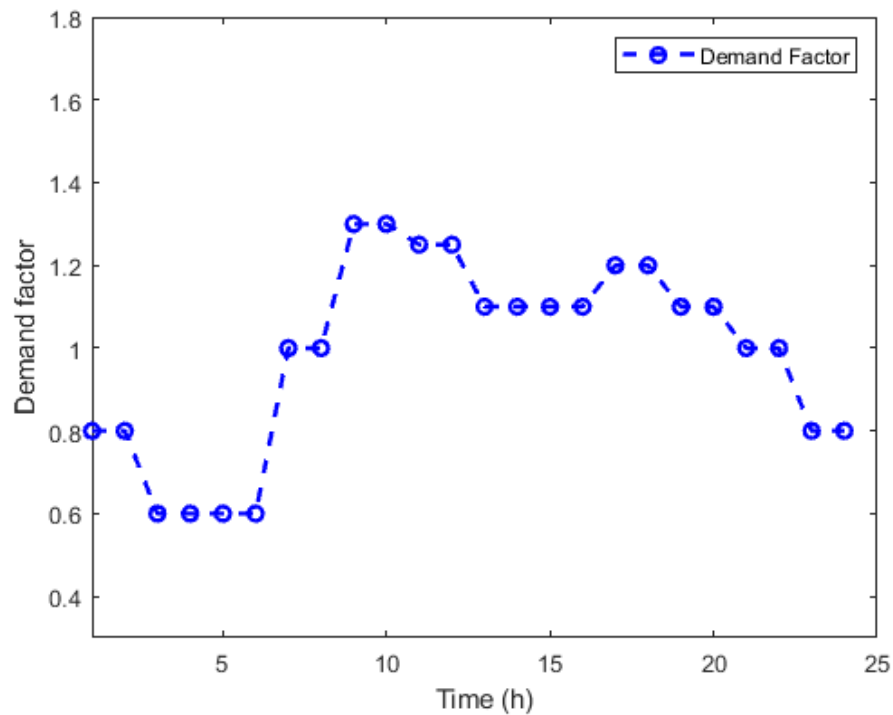


Figure 6.1: Demand factor during multiple periods over 24 hours (Jowitt & Xu, 1990)

Figure 6.1 shows that the demand fluctuates during the day. It can be noted that from 00:00 to 06:00 the demand is lower. The demand picks up after 06:00 and drops significantly after 20:00. It is expected that the PRVs will have most pressure drop during the period from 02:00 to 04:00 because demand is at its lowest during these hours. The effect of the deployment of the proposed RL agent-based scheme is presented in Sections 6.2 and 6.3.

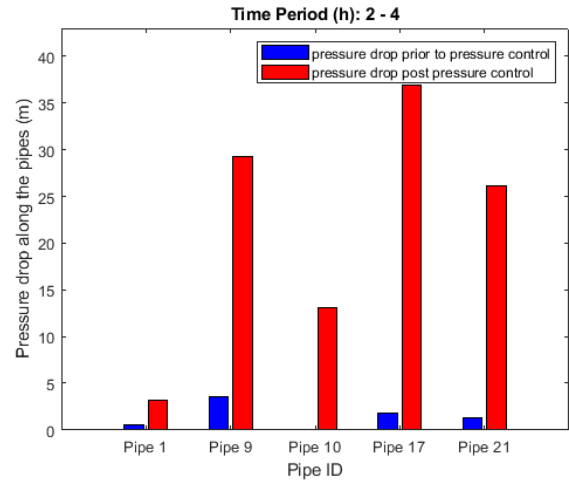
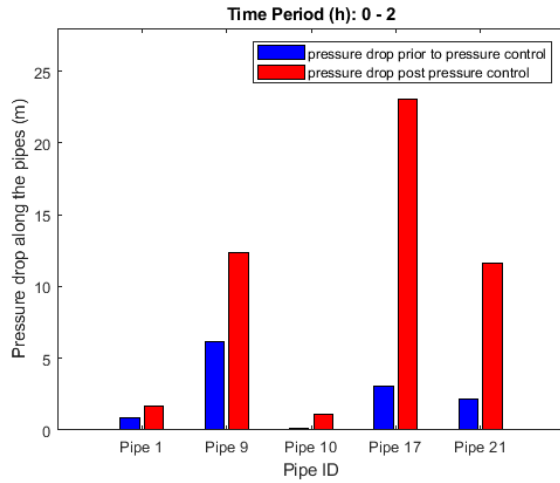
6.2 Numerical Experiment 1

The demand factors in Figure 6.1 are applied on the test case in Figure 5.1. The pressures obtained before and after the utilisation of the scheme in Section 2.3 are presented in Table 6.1.

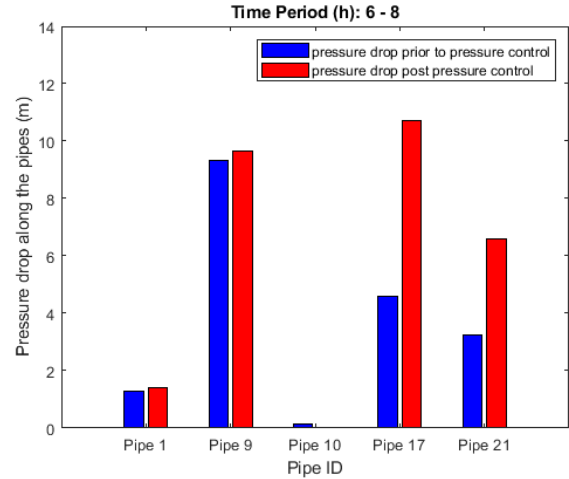
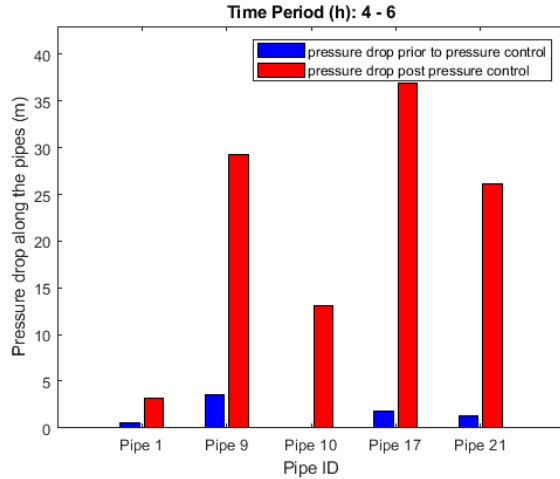
Table 6.1: Pressure observed on the critical node for 24 h period for Case study 1.

Time	h_{CN}	h_{CN}
Period (h)	Prior Control	Tested on a Model
0-2	52.84 m	46.04 m
2-4	56.19 m	25.87 m
4-6	56.19 m	25.87 m
6-8	48.69 m	43.52 m
8-10	41.00 m	46.38 m
10-12	42.40 m	48.46 m
12-14	46.31 m	45.19 m
14-16	46.31 m	45.19 m
16-18	43.76 m	46.84 m
18-20	46.31 m	45.18 m
20-22	48.69 m	43.61 m
22-24	52.84 m	46.04 m

h_{CN} prior Control: Uncontrolled nodal pressure head. h_{CN} RL output tested on a model:
 Testing the control settings from the RL agent on the model.

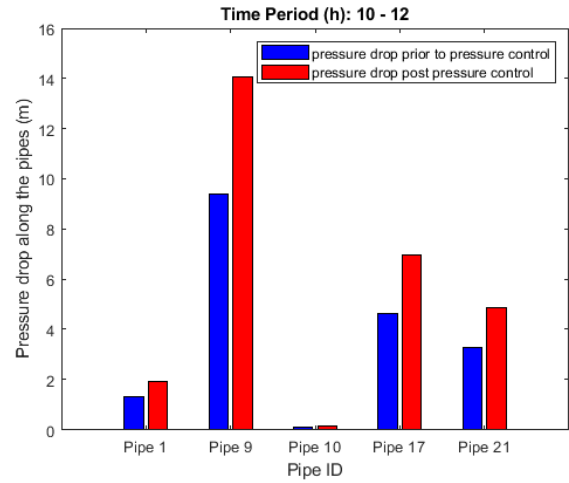
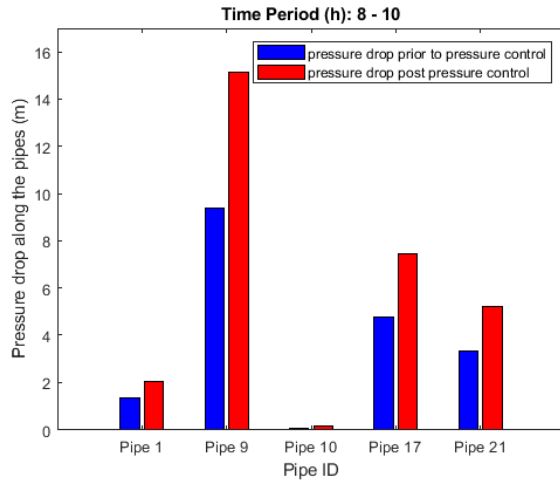


(a) Pressure drop across pipes with PRVs: 00:00 - 02:00 (b) Pressure drop across pipes with PRVs: 02:00 - 04:00

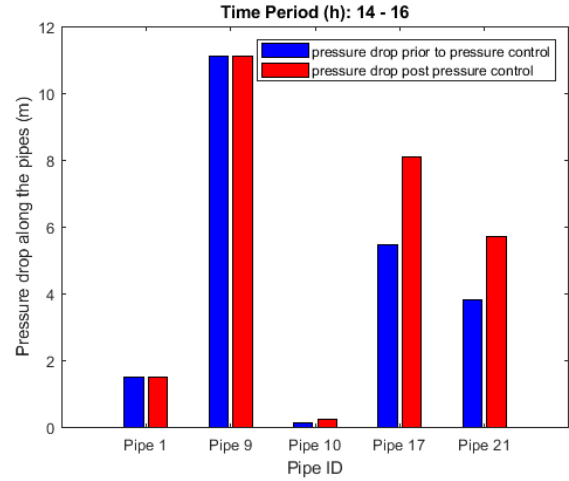
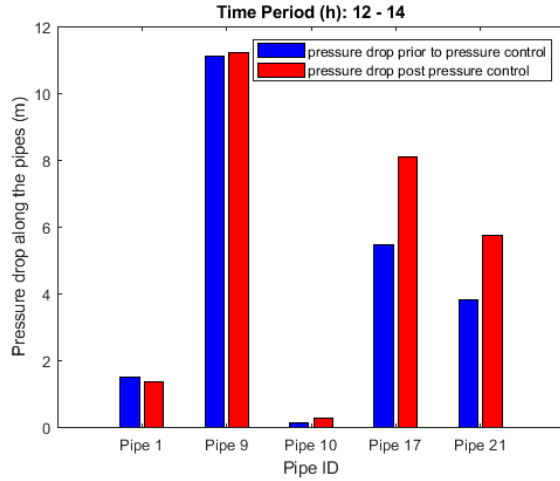


(c) Pressure drop across pipes with PRVs: 04:00 - 06:00 (d) Pressure drop across pipes with PRVs: 06:00 - 08:00

Figure 6.2: Pressure drop across pipes with PRVs for Case study 1 (00:00 - 08:00)

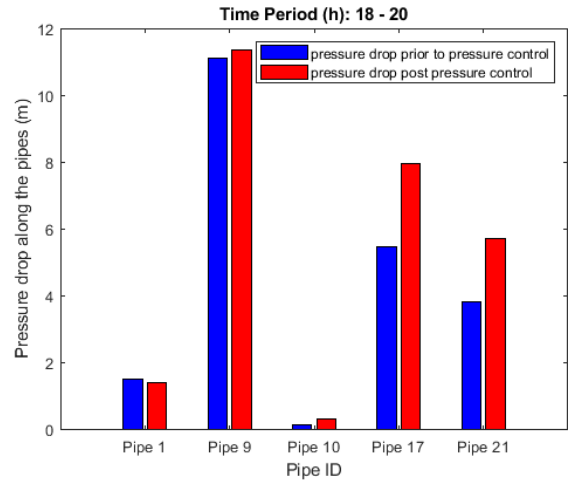
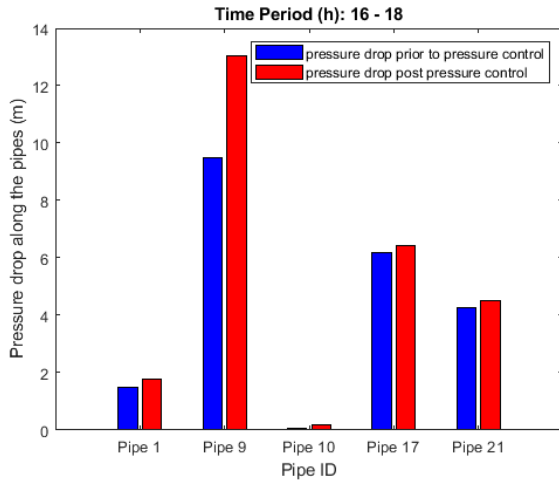


(a) Pressure drop across pipes with PRVs: 08:00 - 10:00 (b) Pressure drop across pipes with PRVs: 10:00 - 12:00

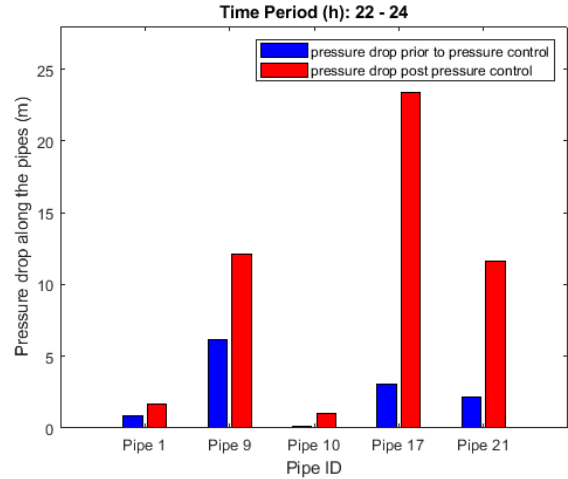
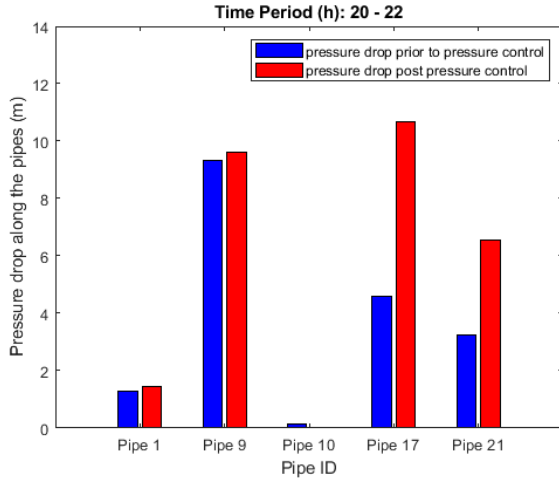


(c) Pressure drop across pipes with PRVs: 12:00 - 14:00 (d) Pressure drop across pipes with PRVs: 14:00 - 16:00

Figure 6.3: Pressure drop across pipes with PRVs for Case study 1 (08:00 - 16:00)



(a) Pressure drop across pipes with PRVs: 16:00 - 18:00 (b) Pressure drop across pipes with PRVs: 18:00 - 20:00



(c) Pressure drop across pipes with PRVs: 20:00 - 22:00 (d) Pressure drop across pipes with PRVs: 22:00 - 24:00

Figure 6.4: Pressure drop across pipes with PRVs for Case study 1 (16:00 - 24:00)

Evidently, the pressure is significantly reduced. Notably, the pressure for the period between 02:00 and 06:00 is reduced by over 50 %. Figures 6.2, 6.3 and 6.4 show pressure drop across the pipes with PRVs. It can be seen in Figures 6.2b and 6.2c that introduction of PRVs significantly increased the pressure. As a result, this reduced the total pressure significantly across the system. The results obtained show consistency with the study carried out in (Adedeji, 2020). This shows the applicability of the scheme proposed in this work for pressure control.

6.3 Numerical Experiment 2

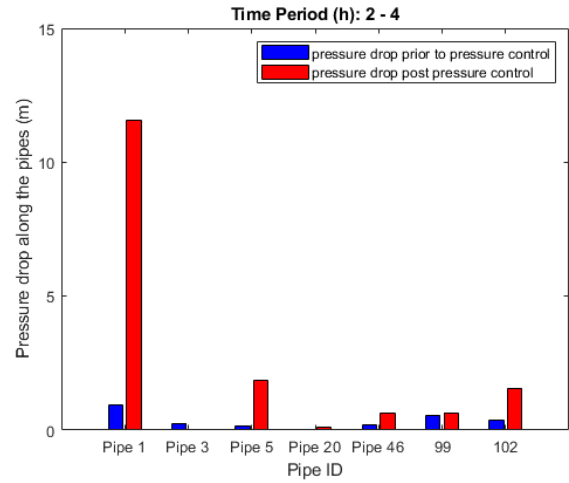
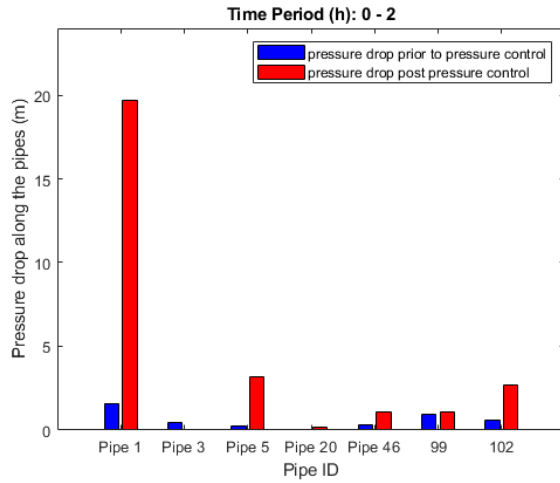
The demand factors in Figure 6.1 are applied to the test case in Figure 5.1. The pressure obtained before and after the utilisation of the scheme in Section 2.3 are presented in Table 6.2.

Table 6.2: Pressure observed on the critical node for 24 h period for Case study 2.

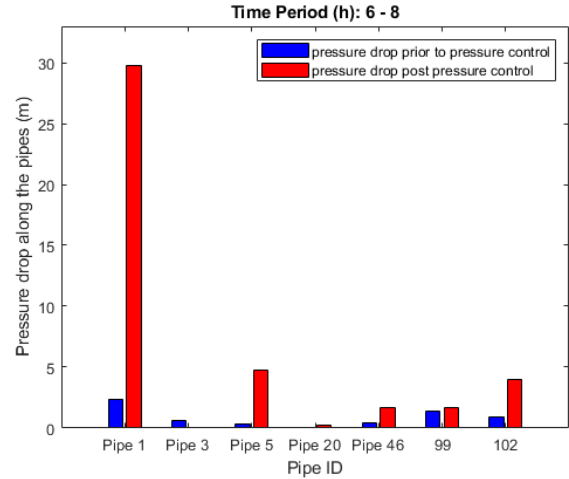
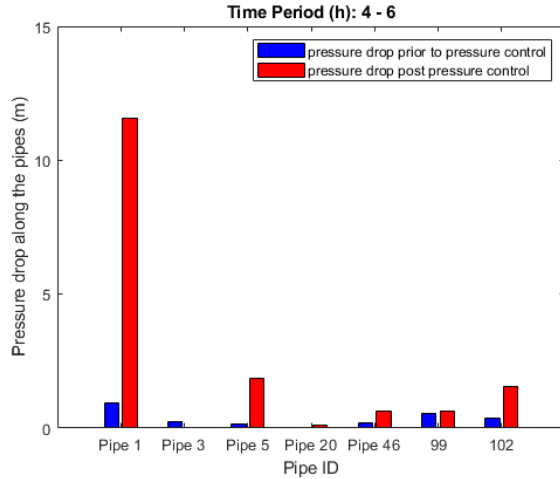
Time	h_{CN}	h_{CN}
Period (h)	Prior Control	Tested on a Model
0-2	79.47 m	62.57 m
2-4	83.82 m	72.07 m
4-6	83.82 m	72.07 m
6-8	74.07 m	62.91 m
8-10	64.11 m	23.28 m
10-12	64.11 m	23.28 m
12-14	71.00 m	41.03 m
14-16	71.00 m	41.03 m
16-18	67.67 m	60.49 m
18-20	71.00 m	32.47 m
20-22	74.07 m	62.91 m
22-24	79.47 m	62.57 m

h_{CN} prior Control: Uncontrolled nodal pressure head. h_{CN} RL output tested on a model: Testing the control settings from the RL agent on the model.

The results obtained conform with the study carried out in (Adedeji, 2020) and therefore show the applicability of the scheme proposed in this work for pressure control. Evidently, the pressure is significantly reduced. Notably, the pressure for the period between 02:00 and 06:00 is reduced by over 50 %. Figures 6.5, 6.6 and 6.7 show pressure drops across the pipes with PRVs. It can be seen in Figures 6.5b and 6.5c the introduction of PRVs significantly increased pressure drop. As a result, this reduced the total pressure significantly across the system's nodes.

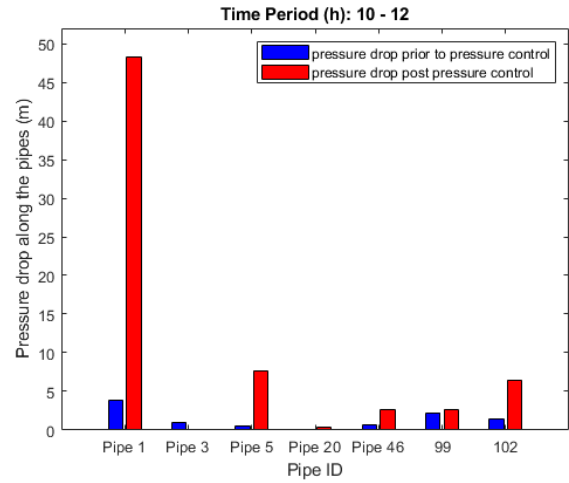
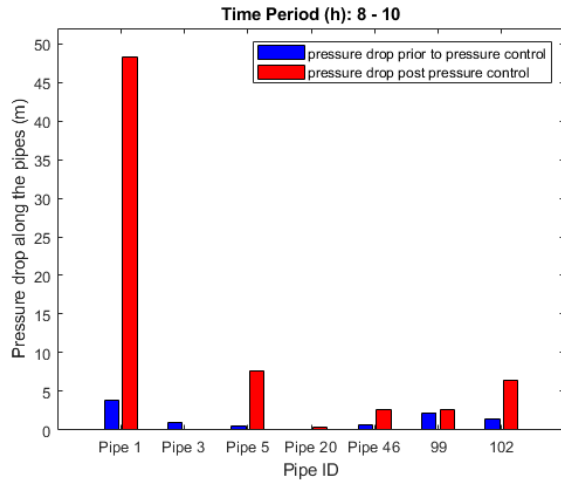


(a) Pressure drop across pipes with PRVs: 00:00 - 02:00 (b) Pressure drop across pipes with PRVs: 02:00 - 04:00

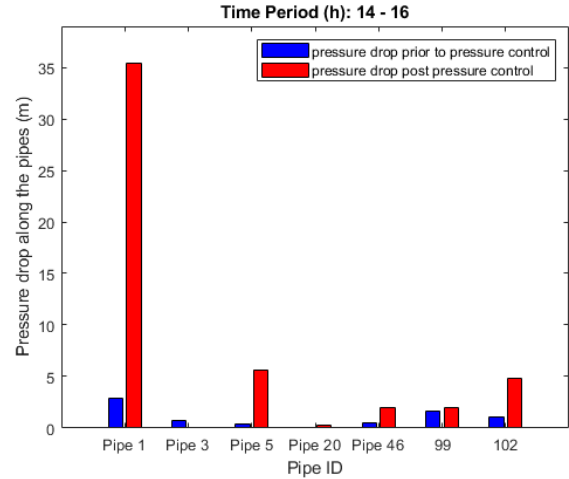
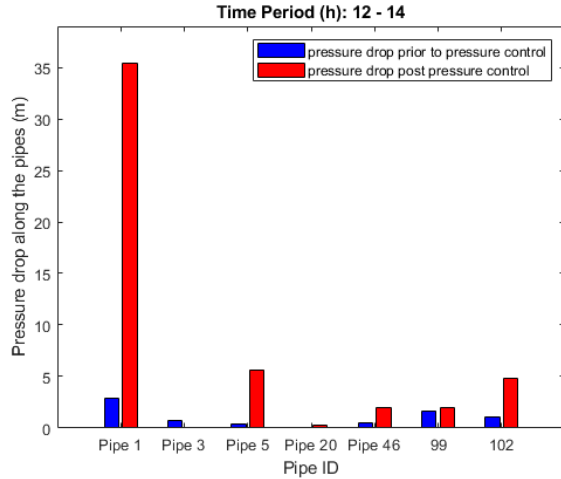


(c) Pressure drop across pipes with PRVs: 04:00 - 06:00 (d) Pressure drop across pipes with PRVs: 06:00 - 08:00

Figure 6.5: Pressure drop across pipes with PRVs for Case study 1 (00:00 - 08:00).

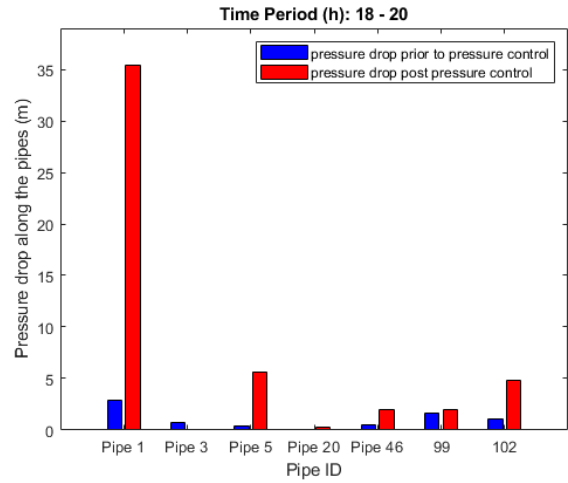
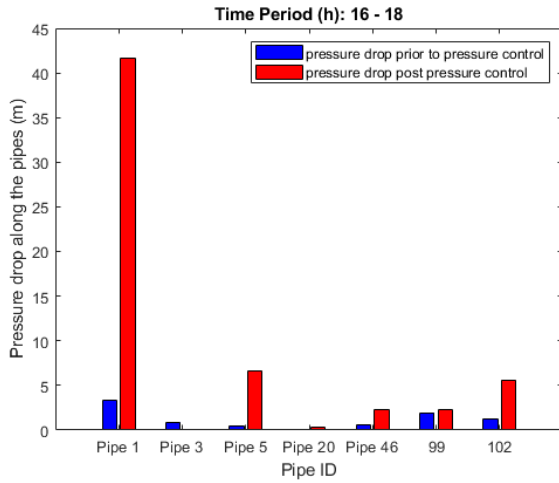


(a) Pressure drop across pipes with PRVs: 08:00 - 10:00 (b) Pressure drop across pipes with PRVs: 10:00 - 12:00

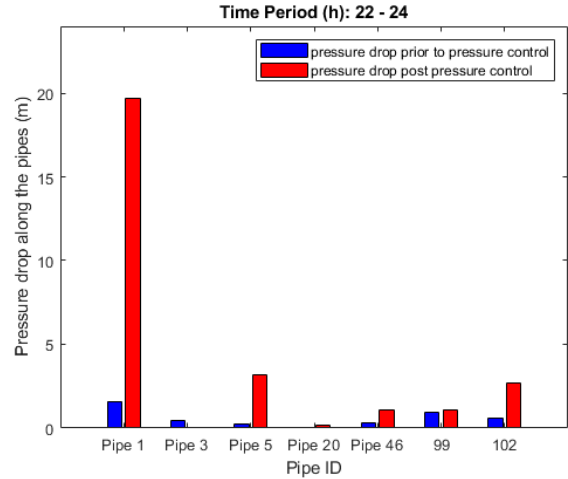
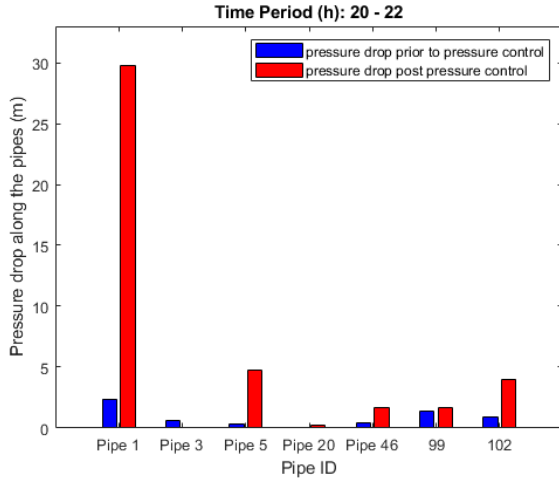


(c) Pressure drop across pipes with PRVs: 12:00 - 14:00 (d) Pressure drop across pipes with PRVs: 14:00 - 16:00

Figure 6.6: Pressure drop across pipes with PRVs for Case study 1 (08:00 - 16:00).



(a) Pressure drop across pipes with PRVs: 16:00 - 18:00 (b) Pressure drop across pipes with PRVs: 18:00 - 20:00



(c) Pressure drop across pipes with PRVs: 20:00 - 22:00 (d) Pressure drop across pipes with PRVs: 22:00 - 24:00

Figure 6.7: Pressure drop across pipes with PRVs for Case study 1 (16:00 - 24:00).

6.4 Summary

The effectiveness of the proposed scheme is investigated in this chapter. The robustness of the scheme is shown by its performance under varying water demand. Variation of the nodal withdrawal is expected due to varying consumer behaviour, but the proposed scheme has shown its adaptive capability. It can be seen in Tables 6.1 and 6.2 that pressure observed at the critical node is considerably reduced post implementation of the RL-based scheme. The critical node is determined according to the criteria set-out in Chapter 4. Figures 6.2, 6.3, 6.4 6.5, 6.6 and 6.7 depict the pressure head drop along the pipes with PRVs installed. It can be seen their installation and operation leads to significantly increased pressure head drop. This will lead to reduced pressure at a downstream node, affecting the entire system. This pressure head drop encapsulates the minor losses of the valves and the losses which result from the operation of the PRVs.

CHAPTER 7. SUMMARY, CONCLUSION AND SUGGESTION FOR FUTURE WORKS

This chapter summarises the thesis and offers concluding remarks. Lastly, some suggestions for future expansion are given.

7.1 Summary

It is widely accepted that pressure control in water distribution networks leads to improved operation of the systems. In Chapter 2, the literature is reviewed concerning pressure control in water distribution networks. Although optimisation methods have been used widely and have shown good results, the computations involved with these methodologies is a concern (Hamam & Hindi, 1992; Rao & Salomons, 2007). Hamam & Hindi (1992); Rao & Salomons (2007) resolved to the utilisation of artificial neural networks (ANNs). However, the need for thousands of dataset points is a major drawback of the method. In addition, perturbation in the water distribution model (i.e incorporating PRVs and/or pumps) affects the convergence properties of their gradient-based solutions. Zou (2019) illustrate this in linear systems.

The mathematical background for the study is presented in Chapter 3. Firstly, the model for water distribution networks is provided with the integration of pressure con-

trol devices. The formulation for the solution of the WDN model is given. Secondly, the optimisation formulation is given in Chapter 3. The optimisation is formulated as a non-linear problem. Lastly, the proposed methodologies are put forward for both the hydraulic simulation and pressure control. The hydraulic simulation emulator is based on quadratic approximation. The matrix formulation of the quadratic formulation is given in Chapter 3. Furthermore, the least-square solution of the quadratic formulation is provided.

Then the model-free control scheme with reinforcement learning is proposed. A reinforcement learning agent receives pressure data from a critical node of the network under test and gives the control input to the PRVs to reduce the pressure. The core algorithm deployed in the methodology is also given. The implementation of mathematical formulations presented in Chapter 3 is given in Chapters 4 and 5. [ch:5]. The appropriateness of the proposed scheme is tested on three networks with the biggest network consisting of 300 nodes and 447 pipes. Evidently, as Zou (2019) suggests, the modification of the steady-state water-distribution model results in the deterioration of its Newton solution. Furthermore, the research carried out sought to test the proposed scheme under varying water demand conditions. This enabled the proper evaluation of the effectiveness of the proposed scheme. The results obtained in Chapter 5 support the findings made in Chapter 4. Consistency with the theories extracted in the literature is observed.

7.2 Conclusion

Thus, this work concludes that

- It is possible to perform the hydraulic simulation of the water distribution networks without solving the non-linear systems of equations in Chapter 3. This was illustrated in this work by the utilisation of a quadratic approximation-based emulator. This was done to avoid the computational complexities that result from the augmented WDN models.
- In this work, a greedy algorithm was used to identify the critical nodes in WDNs. The simulation results showed consistency in two case studies that were used to evaluate the effectiveness of the proposed scheme.
- Although gradient-based optimisation methods seem to be an often-used technique for pressure control, this work illustrates that a non-gradient method can perform this task. This work showed that the utilisation of reinforcement learning for pressure control could perform as well as the gradient-based optimisation procedures. This work used a value iteration algorithm to update the policy of the reinforcement learning agent in order to obtain the best control inputs for PRVs.
- This work showed that the reinforcement learning agent can control PRVs without interaction with WDN models. This is illustrated with the utilisation of a WDN emulator as an environment that interacts with the control agent. The control inputs for PRVs obtained in this arrangement were tested on the model and the results showed consistency with the utilisation of gradient-based optimisation techniques with WDN models.
- Furthermore, the scheme put forward in this work shows that it could be effective

for various demand scenarios. This is shown by the testing of the scheme under varying demand scenarios adopted from [Jowitt & Xu \(1990\)](#).

- The results show that the proposed model-free control based on reinforcement learning can be useful in the event that pressure control is needed while the model is unknown. The only parameters needed would be the reference pressure per demand scenario. This control method could be used in the case of ageing infrastructure, where the parameters of the network components are difficult to estimate due to the deterioration of the system.

7.3 Suggestion for Future Works

The complexities associated with future water distribution networks as a result of interconnections would require unconventional solutions. The recent advances in information communication technologies (ICTs) can provide avenues for prompt and proper management. Furthermore, as the PRVs under excessive pressure generate heat, some energy-trapping devices could be developed to use this energy for another purpose. With innovations such as these, the following ideas could be pursued in the future:

- Information from ICTs could be used to investigate the state and health of WDNs in real time. This innovation could include , but not be limited to, leakage and pressure data for analysis.
- The data obtained from ICTs could be infused into the proposed scheme in this work to control system pressure without the need to model the system
- Pumps can be studied in their use as turbines, as a means of reusing the energy that would ordinarily be dissipated by the PRVs.

- The uncertainties of water demand should be studied as a further problem in pressure control.

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APPENDIX A. IMPACT OF PRESSURE CONTROL ON LEAKAGE FLOWS

A.1 Introduction

Pressure reducing valves (PRVs) are commonly used to control the pressure in water distribution networks (WDNs). Inevitably, this exercise results in reduced leakages in WDNs. In this section, the appraisal of pressure control in leakage flows is investigated.

A.1.1 Leakage Flow Model

Leakages in WDNs occurs in both the nodes and along the pipes. The leakage flow along the pipe could be expressed as

$$q_i = \begin{cases} \beta_i l_i H_i^p, & \text{if } H_i > 0 \\ 0, & \text{if } H_i \leq 0 \end{cases} \quad (\text{A.1})$$

where, β and l are the leakage discharge coefficient and length of the pipe respectively. The mean pressure along the pipe in Equation A.1 is represented by H . For N_b number of the pipes, Equation A.1 can be written is a vectors format as

$$\bar{q} = \begin{cases} \bar{\beta} \bar{l} \bar{H}^p, & \text{if } \bar{H} > 0 \\ 0, & \text{if } \bar{H} \leq 0 \end{cases} \quad (\text{A.2})$$

The topological matrix in Section 3.2 may be used to describe the H as

$$\bar{H}_i = \frac{1}{2} \Psi^T H_i \quad (\text{A.3})$$

where,

$$\Psi = |C| \quad (\text{A.4})$$

Figure A.1 depict the actual total flow in the pipes and the leakage component. It actual flows in the pipes, consist of both the leakages and the useful flow. It can be seen in Figure A.1 that the leakage is actual a fraction of the total flow, however, its continuous nature renders it problematic as the water lost accumulate. Therefore, necessitating the pressure control to minimise the loss.

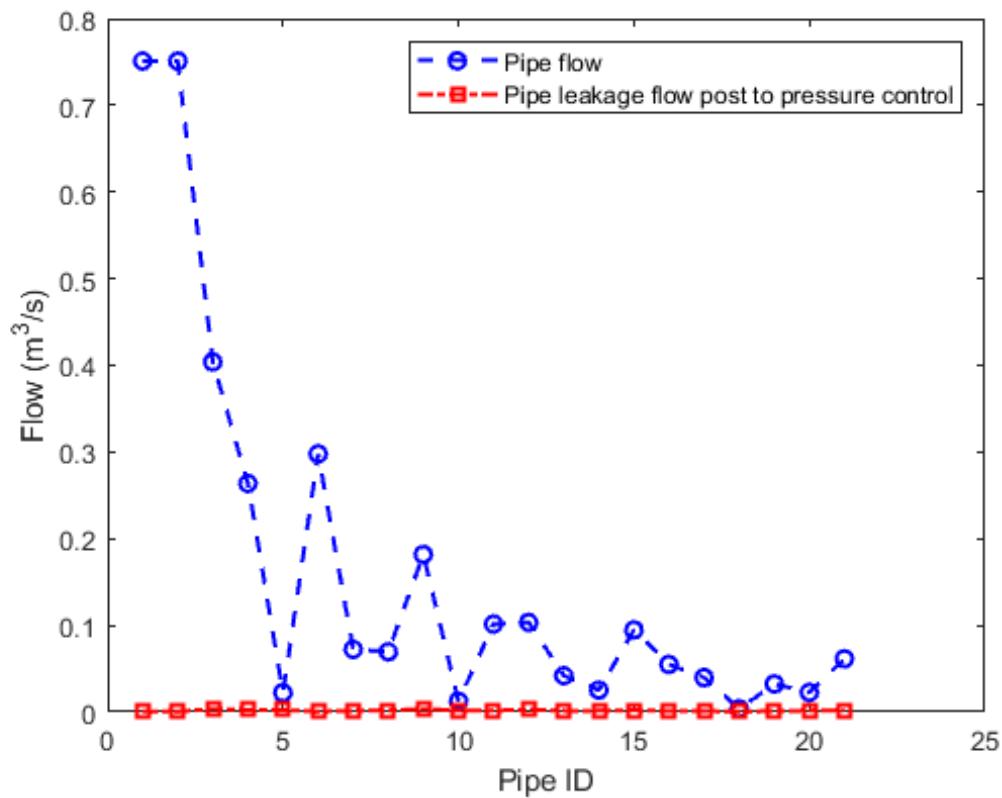
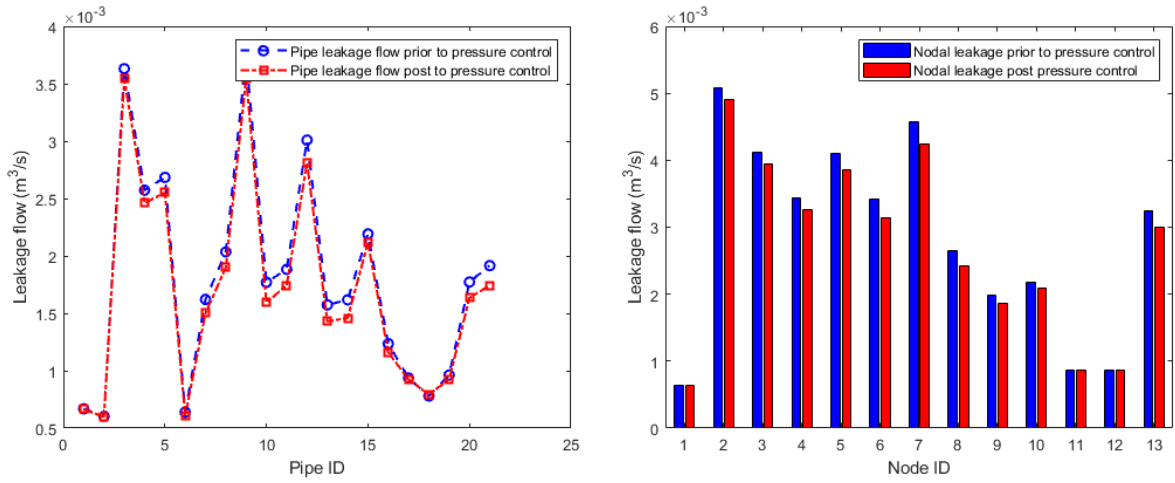


Figure A.1: The actual flow and the leakage flow through the pipes.



(a) Pipes leakages prior and post pressure control. (b) Nodal leakages prior and post pressure control.

Figure A.2: Leakages prior and post pressure control.

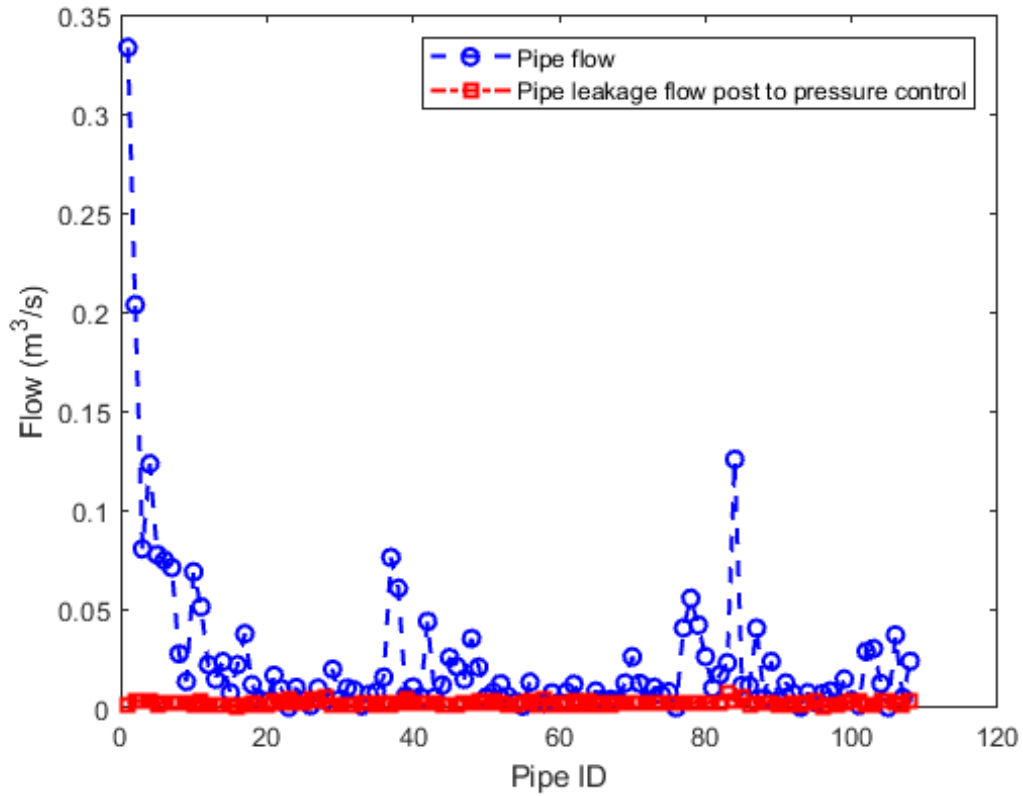
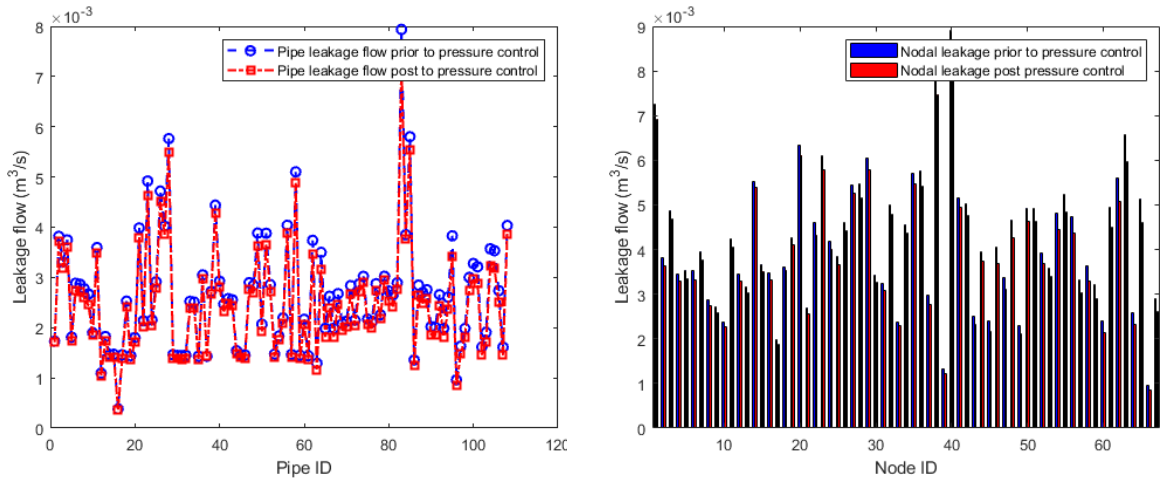


Figure A.3: The actual flow and the leakage flow through the pipes.



(a) Pipes leakages prior and post pressure control. (b) Nodal leakages prior and post pressure control.

Figure A.4: Leakages prior and post pressure control.

In Figures A.2a and A.2b, it can be seen that the leakage flow is considerably reduced after the pressure control. Evidently, pipes 10, 13 and 14 experienced significantly reduced as compared to the other pipes. Nodes 7 and 13 can be seen to show more leakage reduction. This is due to those being at the lower end of pipes with PRVs. In Figure A.3 a proportion of the pipe flow can be seen to be leakages. However, it can be seen that, the leakage flow is a fraction of the total flow. Figures A.4a and A.4b show that, it is possible to reduce the leakage through pressure control. This is depicted by the leakages through the pipes and flowing out of the nodes.

APPENDIX B. EFFECT OF PRVs ON THE SOLUTION OF THE WDNs

In this Section, the effect of the introduction of PRVs on the steady state model of the model is given. Tables B.1 and B.2 shows the number of iteration it takes to solution convergence.

Table B.1: Number of iteration for solution convergence with 80%, 100% and 120% demand on Case Study 1.

Loading Levels	Iterations Without PRVs	Iterations With PRVs
80%	4	5
100%	4	5
120%	4	4

Table B.2: Number of iteration for solution convergence with 80%, 100% and 120% demand on Case Study 2.

Loading Levels	Iterations Without PRVs	Iterations With PRVs
80%	6	9
100%	6	7
120%	6	8

Evidently, consistent with [Zou \(2019\)](#), the modification of the steady state model resulted in slight deterioration of the solution.

APPENDIX C. PARAMETERS OF THE NETWORKS

C.1 Case study network 1 parameters

C.1.1 Pipe data

Table C.1: Pipe data for the case study network 1 ([Ozger & Mays, 2003](#))

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Chw
1	14	1	609.90	762	130
2	1	2	243.80	762	128
3	2	3	1524	609	126
4	3	4	1127.76	609	124
5	5	4	1188.72	609	122
6	15	5	640.08	406	120
7	4	6	762.00	254	118
8	3	7	944.88	254	116
9	2	7	1676.40	381	114
10	7	6	883.92	305	112
11	5	6	883.92	305	110
12	5	13	1371.60	381	108
13	13	6	762.00	254	106

Table C.1: Pipe data for the case study network 1 ([Ozger & Mays, 2003](#)) (*Cont.*)

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Chw
14	7	8	822.96	254	104
15	2	10	944.88	305	102
16	10	9	579.00	305	100
17	10	11	487.68	203	98
18	11	12	457.20	152	96
19	9	12	502.92	203	94
20	9	8	883.92	203	92
21	13	8	944.88	305	90

C.1.2 Node data

Table C.2: Node data for the case study network 1 [Ozger & Mays \(2003\)](#)

Node ID	Elevation (m)	Demand L/s)
1	27.43	0
2	33.53	59
3	28.96	59
4	32.00	178
5	30.48	59
6	31.39	190
7	29.56	178
8	31.39	91
9	32.61	0
10	34.14	0
11	35.05	30
12	36.58	30
13	33.53	0
14	60.96	Source Node
15	60.96	Source Node

C.2 Case study network 2 parameters

C.2.1 Pipe data

Table C.3: Pipe data for the case study network 2

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Chw	Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Chw
1	1	15	1000	0.6	120	55	26	35	600	0.15	100
2	15	28	1000	0.45	120	56	27	33	1100	0.25	120
3	28	27	894	0.45	120	57	33	34	400	0.15	100
4	28	30	1020	0.45	120	58	30	35	1400	0.15	100
5	30	31	500	0.45	120	59	33	32	400	0.15	100
6	31	45	800	0.45	120	60	31	32	600	0.15	100
7	45	51	800	0.45	120	61	30	29	400	0.15	100
8	51	57	800	0.2	120	62	29	44	1100	0.15	100
9	57	58	800	0.2	120	63	44	46	400	0.15	100
10	15	14	500	0.25	120	64	46	47	1077	0.15	100
11	15	4	949	0.25	120	65	48	47	600	0.15	100
12	4	5	300	0.25	120	66	47	50	800	0.15	100
13	11	5	500	0.25	120	67	49	50	600	0.15	100
14	14	11	400	0.25	120	68	49	48	800	0.15	100
15	14	16	400	0.25	120	69	51	48	600	0.15	100
16	16	27	104	0.25	120	70	51	52	600	0.25	120
17	14	13	400	0.25	120	71	52	43	800	0.20	120
18	13	12	700	0.25	120	72	45	43	600	0.15	100
19	12	9	400	0.25	120	73	43	32	800	0.20	120
20	9	8	500	0.25	120	74	33	42	825	0.25	120
21	8	5	1100	0.25	120	75	42	43	600	0.15	100
22	8	7	600	0.15	120	76	53	52	600	0.25	120
23	6	7	1400	0.15	120	77	42	53	800	0.25	120
24	4	6	600	0.15	100	78	41	42	600	0.25	120
25	3	4	800	0.15	100	79	41	36	800	0.25	120
26	3	2	1300	0.15	100	80	37	39	800	0.25	120
27	16	2	1100	0.20	120	81	39	40	800	0.15	120
28	2	29	1600	0.15	100	82	41	39	800	0.15	100
29	16	17	400	0.20	120	83	39	64	2400	0.25	120
30	17	13	400	0.20	120	84	70	41	2262	0.45	120
31	13	10	400	0.20	120	85	41	54	1600	0.15	100
32	10	11	400	0.15	120	86	55	54	400	0.20	120
33	10	9	700	0.15	100	87	53	55	825	0.25	120
34	18	17	700	0.15	100	88	56	55	800	0.20	120
35	12	18	400	0.15	100	89	52	56	800	0.20	120
36	19	12	800	0.15	100	90	57	56	600	0.20	120
37	69	19	806	0.45	120	91	57	49	600	0.20	120
38	19	21	700	0.25	120	92	49	59	800	0.20	120
39	21	20	1200	0.15	100	93	58	59	600	0.15	100
40	21	22	800	0.15	100	94	59	60	800	0.15	100
41	22	23	700	0.15	100	95	60	61	1200	0.15	100
42	21	24	700	0.25	120	96	68	61	300	0.15	100
43	20	26	700	0.20	120	97	62	68	500	0.15	100

Table C.3: Pipe data for the case study network 2 (*Cont.*)

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Chw	Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Chw
44	17	20	424	0.20	120	98	58	62	600	0.15	100
45	27	26	400	0.25	120	99	56	62	900	0.20	120
46	26	25	400	0.25	120	100	63	62	1000	0.15	100
47	24	25	800	0.25	120	101	66	68	1000	0.15	100
48	24	23	800	0.25	120	102	63	66	500	0.25	120
49	23	38	1118	0.25	120	103	66	67	600	0.25	120
50	38	37	600	0.25	120	104	63	64	1100	0.25	120
51	24	37	1100	0.15	100	105	66	65	1100	0.15	100
52	37	36	800	0.15	100	106	55	63	825	0.25	120
53	34	36	400	0.15	100	107	64	65	500	0.15	120
54	34	35	500	0.15	100	108	25	36	1100	0.25	120

Table C.4: Node data for the case study network 2

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
1	90	Source Node	36	57	0
2	78	5.00	37	55	0
3	72	5.00	38	56	15.0
4	63	15.0	39	62	10.0
5	60	20.0	40	57	10.0
6	60	10.0	41	62	0.0
7	64	10.0	42	55	0.0
8	65	10.0	43	49	10.0
9	65	0.0	44	55	15.0
10	55	20.0	45	50	0.0
11	61	0	46	58	0.0
12	65	15.0	47	55	10.0
13	55	20.0	48	50	0.0
14	61	0	49	48	5.0
15	69	10.0	50	50	0.0
16	62	0	51	49	5.0
17	55	20.0	52	46	15.0
18	62	15.0	53	53	0.0
19	74	0	54	59	0.0
20	55	0	55	56	10.0
21	70	0	56	47	10.0
22	72	5.0	57	44	5.0
23	70	20.0	58	42	10.0
24	66	15.0	59	45	0.0
25	59	30.0	60	40	5.0
26	55	0	61	45	10.0
27	58	20.0	62	48	5.0

Table C.4: Node data for the case study network 2 (*Cont.*)

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
28	67	0	63	55	0.0
29	63	0	64	68	30.0
30	62	40.0	65	68	5.0
31	58	0.0	66	55	0.0
32	51	0	67	55	30.0
33	51	15.0	68	45	0.0
34	55	0	69	90	Source Node
35	55	0	70	90	Source Node

C.3 Case study network 3 parameters

C.3.1 Node data

Table C.5: Node data for the case study 3

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
1	0.0	180	25	3.0	135
2	0.0	165	26	3.0	130
3	0.0	150.5	27	3.0	129.5
4	3.0	149.5	28	3.0	127
5	3.0	154	29	1.0	150
6	3.0	153	30	3.0	149.5
7	3.0	146	31	3.0	145
8	3.0	143	32	3.0	139.5
9	3.0	146	33	3.0	134
10	3.0	143	34	3.0	129.5
11	0.0	130	35	3.0	128
12	3.0	148	36	3.0	127
13	3.0	143	37	3.0	124
14	3.0	141	38	3.0	123
15	0.0	145	39	8.0	145
16	0.0	137	40	7.0	140
17	0.0	128	41	3.0	130
18	3.0	149.5	42	3.0	127
19	3.0	142.5	43	3.0	125.5
20	0.0	135	44	3.0	124
21	3.0	129.5	45	5.5	140
22	3.0	127	46	3.0	137
23	3.0	149	47	6.5	135
24	3.0	140	48	7.0	132

Table C.5: Node data for the case study 3 (*Cont.*)

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
49	3.0	129	73	3.0	131
50	3.0	126.5	74	3.0	130.5
51	3.0	125.5	75	3.0	131
52	3.0	125	76	3.0	130.5
53	3.0	123	77	3.0	130
54	3.0	122	78	3.0	130
55	3.0	135	79	3.0	135
58	3.0	131	80	8.0	135
57	3.0	129	81	3.0	135
58	3.0	126	82	3.0	135
59	3.0	125	83	3.0	137.5
60	3.0	125	84	9.0	138
61	3.0	122	85	3.0	135
62	6.0	135	86	3.0	135
63	5.0	132	87	3.0	143
64	3.0	129.5	88	3.0	145
65	3.0	129	89	3.0	144
66	3.0	128.5	90	3.0	141
67	3.0	128.5	91	3.0	139
68	3.0	128	92	3.0	143
69	3.0	135	93	3.0	146
70	3.0	131	94	3.0	146.5
71	3.0	130.5	95	3.0	147
72	3.0	130.5	96	3.0	150

Table C.5: Node data for the case study 3 (*Cont.*)

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
97	3.0	140	121	3.0	123
98	3.0	139.5	122	3.0	127
99	3.0	139	123	3.0	130
100	3.0	137	124	3.0	125
101	3.0	140.5	125	3.0	125
102	0.0	145	126	3.0	126
103	3.0	140	127	3.0	131
104	3.0	135	128	3.0	128
105	3.0	137	129	3.0	129.5
106	3.0	139	130	3.0	130
107	3.0	135	131	3.0	130.5
108	3.0	144	132	3.0	135
109	3.0	140	133	3.0	139
110	0.0	155	134	3.0	135
111	3.0	170	135	3.0	145
112	3.0	152	136	3.0	138
113	3.0	136	137	3.0	131
114	0.0	125	138	3.0	131
115	0.0	123	139	3.0	133
116	0.0	120.5	140	3.0	133
117	3.0	127	141	3.0	133
118	3.0	123	142	3.0	134
119	3.0	123	143	3.0	134
120	3.0	123	144	3.0	133

Table C.5: Node data for the case study 3 (*Cont.*)

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
145	3.0	133	169	3.0	76
146	3.0	132	170	3.0	76
147	3.0	129.5	171	3.0	77
148	3.0	129.5	172	3.0	76
149	3.0	129	173	3.0	75
150	3.0	124	174	3.0	74
151	0.0	120.5	175	3.0	73
152	3.0	122	176	3.0	73
153	3.0	120.5	177	3.0	74
154	3.0	130	178	10.0	72
155	3.0	127	179	3.0	70
156	3.0	131	180	3.0	70.5
157	3.0	133	181	3.0	69.5
158	3.0	131	182	3.0	79.5
159	3.0	132	183	3.0	78
160	3.0	128	184	3.0	77
161	3.0	130	185	3.0	74
162	3.0	122	186	3.0	74
163	3.0	123	187	3.0	70
164	0.0	180	188	3.0	70.5
165	3.0	129.5	189	3.0	76
166	3.0	78	190	3.0	80
167	3.0	77	191	3.0	76
168	3.0	75	192	4.5	76

Table C.5: Node data for the case study 3 (*Cont.*)

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
193	4.5	75	217	3.0	69.5
194	7.0	73	218	3.0	69
195	9.0	77	219	3.0	68
196	6.5	76.5	220	3.0	67.5
197	7.0	74	221	3.0	67.5
198	5.0	79	222	3.0	68
199	3.0	78	223	3.0	67.5
200	3.0	76	224	3.0	68
201	3.0	74	225	3.0	77
202	3.0	74	226	3.0	70
203	3.0	70	227	3.0	67
204	3.0	69.5	228	3.0	65
205	3.0	69	229	3.0	66
206	3.0	70	230	3.0	65.5
207	3.0	73	231	3.0	65
208	3.0	73	232	3.0	65
209	3.0	71	233	3.0	65
210	3.0	71.5	234	3.0	65.5
211	3.0	73	234	3.0	67
212	3.0	73.5	236	3.0	68
213	3.0	62.5	237	3.0	68
214	3.0	69.5	238	6.0	67
215	3.0	70	239	6.0	66
216	3.0	69.5	240	3.0	66

Table C.5: Node data for the case study 3 (*Cont.*)

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
241	3.0	63	265	3.0	61.5
242	3.0	63	266	3.0	62
243	3.0	63	267	3.0	62
244	3.0	62.5	268	6.0	61.5
245	3.0	74	269	3.0	72
246	3.0	69.5	270	3.0	69.5
247	3.0	66	271	3.0	62.5
248	3.0	64	272	3.0	61
249	3.0	62	273	3.0	58
250	3.0	61	274	3.0	55
251	3.0	62	275	1.0	55.5
252	3.0	61.5	276	1.0	56
253	3.0	63	277	1.0	57
254	3.0	69	278	3.0	60
255	3.0	66	279	3.0	58
256	3.0	64	280	3.0	60
257	3.0	60	281	3.0	61
258	3.0	59	282	3.0	61.5
259	1.0	59	283	6.0	61
260	3.0	61	284	6.0	65
261	1.0	59	285	3.0	72
262	3.0	60.5	286	3.0	62
263	3.0	61	287	3.0	57
264	3.0	61	288	3.0	53
289	3.0	62	295	3.0	56
290	3.0	72	296	3.0	56

Table C.5: Node data for the case study 3 (*Cont.*)

Node ID	Elevation (m)	Demand L/s)	Node ID	Elevation (m)	Demand L/s)
291	3.0	52	297	3.0	52
292	3.0	52	298	0.0	78
293	3.0	53	299	0.0	72
294	3.0	57	300	0.0	40

C.3.2 Pipes data

Table C.6: Pipe data for the case study network 3

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)
1	1	2	1500	600	25	18	19	600	150
2	2	3	700	450	26	15	19	400	150
3	3	4	550	200	27	16	20	400	450
4	4	5	600	200	28	17	23	400	150
5	5	6	300	200	29	18	23	300	150
6	6	7	600	100	30	23	24	800	150
7	9	7	300	150	31	25	24	400	150
8	7	8	200	150	32	25	20	300	450
9	10	8	300	150	33	27	21	500	150
10	8	11	1100	150	34	20	21	500	150
11	5	9	600	150	35	21	22	400	150
12	13	9	600	150	36	28	22	500	150
13	14	10	600	150	37	23	31	700	150
14	4	12	200	150	38	24	32	800	150
15	12	13	400	150	39	33	25	700	450
16	13	14	200	150	40	25	26	400	150
17	15	12	400	150	41	26	27	100	150
18	16	14	400	150	42	34	27	500	150
19	17	11	700	450	43	27	28	400	150
20	3	15	600	450	44	36	28	500	150
21	15	16	600	450	45	30	29	700	150
22	16	17	900	450	46	30	31	700	100
23	2	30	1400	200	47	32	31	500	150
24	3	18	400	150	48	33	32	700	150
49	33	34	500	150	73	46	47	700	150
50	34	35	200	150	74	48	47	500	150
51	35	36	200	150	75	49	48	750	150
52	36	37	500	150	76	49	50	500	150
53	38	37	200	150	77	50	51	200	150
54	29	45	1400	100	78	51	52	200	150
55	30	39	500	150	79	52	53	500	150
56	31	40	500	100	80	53	54	500	150
57	48	32	1300	150	81	45	62	1100	150
58	41	33	700	450	82	46	55	600	150
59	35	42	700	150	83	47	56	700	150
60	43	36	700	150	84	57	49	1000	450
61	44	37	700	150	85	50	58	600	100
62	54	38	1000	150	86	58	59	400	100
63	39	40	700	150	87	52	59	600	100
64	40	47	800	100	88	53	60	900	100

Table C.6: Pipe data for the case study network 3 (*Cont.*)

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)
65	41	42	700	150	89	61	54	950	100
66	42	43	200	150	90	63	62	700	150
67	43	44	500	150	91	55	56	700	150
68	39	46	900	150	92	57	56	900	150
69	49	41	300	450	93	76	59	1300	100
70	51	42	300	150	94	61	60	700	100
71	52	43	300	150	95	69	62	600	150
72	46	45	700	150	96	63	70	600	150
97	64	56	700	150	121	84	83	700	150
98	66	65	500	150	122	85	84	700	450
99	66	67	200	150	123	86	85	900	450
100	64	67	900	150	124	75	86	600	450
101	73	64	400	150	125	75	76	900	200
102	74	67	400	150	126	76	77	500	200
103	75	68	800	450	127	77	78	900	200
104	68	66	350	150	128	83	87	1000	150
105	77	60	800	100	129	84	88	1000	150
106	78	61	600	100	130	85	89	800	200
107	70	69	700	150	131	90	91	320	150
108	69	79	500	150	132	97	90	450	150
109	70	80	500	150	133	97	98	350	150
110	71	70	200	150	134	86	98	600	150
111	72	71	300	150	135	99	100	250	150
112	71	81	500	150	136	98	99	340	150
113	81	82	300	150	137	99	101	310	150
114	72	82	500	150	138	102	75	1300	450
115	73	72	200	150	139	105	104	500	150
116	74	73	900	150	140	106	103	430	150
117	75	74	300	150	141	106	105	170	150
118	80	79	700	150	142	105	107	750	150
119	79	83	600	150	143	77	107	410	150
120	84	80	600	150	144	108	106	350	150
145	102	108	720	450	169	114	115	500	450
146	108	109	1100	450	170	115	116	800	450
147	109	78	700	450	171	117	118	800	150
148	113	114	1100	150	172	116	151	2000	450
149	88	87	700	150	173	150	151	500	450
150	93	88	600	150	174	78	114	600	450
151	89	93	500	200	175	123	117	500	150
152	89	92	400	150	176	119	125	400	150

Table C.6: Pipe data for the case study network 3 (*Cont.*)

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)
153	92	94	500	150	177	120	126	400	150
154	94	93	400	150	178	121	122	500	150
155	95	92	800	150	179	120	121	400	150
156	95	97	700	150	180	119	120	600	150
157	95	96	500	150	181	118	119	300	150
158	96	94	800	150	182	123	124	1100	150
159	102	95	900	150	183	127	123	200	150
160	110	102	700	450	184	128	124	200	150
161	112	108	700	150	185	127	128	1100	450
162	113	109	720	150	186	125	126	600	150
163	111	96	1400	150	187	128	147	1400	450
164	111	110	480	750	188	147	150	680	450
165	164	111	700	750	189	150	152	600	150
166	110	112	700	450	190	152	149	600	150
167	112	113	1500	450	191	152	153	700	150
168	113	127	500	450	192	153	155	900	150
193	127	132	600	300	217	136	135	1100	150
194	129	130	600	150	218	142	136	900	200
195	128	129	300	150	219	139	140	200	150
196	129	131	300	150	220	140	141	200	150
197	147	146	600	200	221	145	141	500	150
198	154	155	700	150	222	141	142	500	150
199	155	165	300	150	223	143	142	500	200
200	154	156	300	150	224	144	143	400	200
201	156	165	700	150	225	145	144	100	200
202	132	133	500	300	226	144	157	900	150
203	131	132	1100	150	227	157	158	700	150
204	131	134	500	150	228	143	159	1600	200
205	131	137	500	150	229	158	160	600	150
206	138	137	200	150	230	159	161	600	150
207	146	138	700	150	231	158	159	500	150
208	146	156	900	150	232	160	161	500	150
209	165	158	500	150	233	160	162	600	150
210	137	139	500	150	234	163	162	500	150
211	138	140	500	150	235	161	163	600	150
212	146	145	500	200	236	151	298	1300	450
213	156	157	600	150	237	11	299	2000	450
214	133	135	500	150	238	167	166	200	100
215	134	133	1100	300	239	168	167	500	100
216	134	136	500	300	240	169	168	1000	100

Table C.6: Pipe data for the case study network 3 (*Cont.*)

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)
241	169	170	500	100	266	192	193	400	150
243	170	171	300	100	267	193	194	400	150
244	171	172	500	100	268	193	196	800	150
245	172	173	1000	100	269	194	197	800	150
246	173	174	500	300	270	195	196	400	150
247	174	175	500	300	271	196	197	400	150
248	175	180	700	100	272	195	199	800	300
249	180	181	300	100	273	196	200	800	150
250	173	182	1100	300	274	197	201	800	100
251	174	183	1100	100	275	198	199	300	150
252	175	185	500	300	276	199	200	400	150
253	185	187	900	100	277	200	201	400	150
254	185	186	200	300	278	202	166	1000	100
255	186	188	880	100	279	204	167	700	100
256	181	187	500	100	280	205	168	700	100
257	187	188	200	100	281	169	206	600	450
258	188	194	800	100	282	207	208	300	100
259	183	184	400	200	283	208	209	300	100
260	184	189	300	100	284	208	170	300	100
261	184	191	400	200	285	171	209	300	100
262	189	192	400	300	286	210	209	300	100
263	192	191	300	150	287	209	212	500	100
264	191	198	1600	200	288	211	212	300	100
265	192	195	800	300	289	212	172	300	100
290	235	173	1450	300	314	205	220	400	100
291	236	213	900	100	315	220	221	400	100
292	175	213	780	100	316	221	222	200	100
293	175	237	1400	100	317	221	223	400	150
294	238	214	900	100	318	223	224	200	150
295	214	180	600	100	319	206	231	800	300
296	239	181	1400	100	320	207	233	800	100
297	202	225	1050	100	321	226	225	500	100
298	216	215	400	100	322	227	226	800	100
299	217	216	200	100	323	240	227	300	200
300	218	217	300	100	324	227	228	500	100
301	203	218	400	100	325	228	241	300	100
302	203	202	600	450	326	228	229	400	100
303	204	203	300	450	327	230	229	400	100
304	205	204	500	450	328	230	243	200	100
305	206	205	1000	450	329	231	230	600	100
306	206	207	500	450	330	244	243	600	100
307	207	210	300	450	331	231	244	200	300

Table C.6: Pipe data for the case study network 3 (*Cont.*)

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)
308	210	211	500	450	332	231	232	200	100
309	211	234	850	100	333	232	233	300	100
310	218	219	400	100	334	232	251	500	100
311	219	220	400	100	335	233	234	500	100
312	219	228	300	100	336	252	234	500	100
313	220	229	300	100	337	235	234	800	100
338	235	236	900	100	362	247	255	300	100
339	236	237	600	100	363	247	248	500	300
340	237	238	400	100	364	248	249	800	300
341	248	239	600	100	365	248	256	300	100
342	245	225	700	100	366	249	257	500	100
343	246	226	700	100	367	249	250	600	300
344	247	240	400	200	368	260	250	200	100
345	240	241	500	100	369	260	262	1000	100
346	248	241	400	100	370	252	262	400	100
347	249	242	200	100	371	263	262	800	100
348	242	243	100	100	372	263	264	100	300
349	244	250	300	300	373	264	265	500	300
350	250	251	200	300	374	265	266	400	300
351	251	252	800	300	375	266	267	600	300
352	252	253	700	300	376	267	281	700	100
353	264	253	300	300	377	267	268	400	300
354	253	235	500	300	378	268	282	600	200
355	266	236	800	100	379	282	283	300	200
356	267	237	800	100	380	283	284	1000	200
357	268	238	800	100	381	295	283	600	100
358	269	245	800	300	382	296	239	2000	100
359	245	246	500	300	383	270	254	500	100
360	246	254	300	100	384	255	254	900	100
361	246	247	800	300	385	255	271	500	100
386	256	272	500	100	410	279	280	500	100
387	256	257	800	100	411	280	281	1000	100
388	257	273	650	100	412	294	281	500	100
389	258	257	600	100	413	285	290	800	100
390	274	258	500	100	414	290	289	1300	100
391	258	259	400	100	416	289	288	800	100
392	258	260	300	100	417	286	287	800	100
393	259	261	400	100	418	271	286	300	100
394	277	261	300	100	419	285	286	1300	100
395	259	275	500	100	420	287	291	1100	100
396	276	277	200	150	421	274	291	500	100

Table C.6: Pipe data for the case study network 3 (*Cont.*)

Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)	Pipe ID	Start Node	End Node	Length (m)	Diameter (mm)
397	278	277	1000	100	422	291	292	400	100
398	279	278	200	300	423	275	292	500	100
399	278	263	400	300	424	293	292	1400	100
400	280	265	700	100	425	293	279	500	300
401	285	269	300	300	426	293	294	1500	100
402	269	270	400	100	427	294	295	700	100
403	270	271	900	100	428	295	296	300	100
404	271	272	500	100	429	297	293	200	300
405	272	273	400	100	430	286	289	800	100
406	274	273	1000	100	431	287	288	600	100
407	274	275	400	100	432	300	297	500	450
408	275	276	400	100	433	147	148	300	200
409	279	276	1000	100	434	148	149	600	200
435	149	154	300	100	442	190	191	900	300
436	212	177	500	100	443	186	189	400	300
437	178	177	300	450	444	182	183	500	200
438	211	178	500	450	445	177	173	550	450
439	235	179	550	100	446	124	125	150	100
440	213	176	270	100	447	68	57	300	450
441	182	190	400	300					