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Pressure, Leakage and Energy Management in Water Distribution Systems

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Abstract

A fast and efficient method to calculate time schedules for internal and boundary PRVs and flow modulation curves has been developed and implemented. Both time and flow modulation can be applied to a single inlet DMA. The time modulation methodology is based on solving a nonlinear programming problem (NLP). In addition, Genetic Algorithms (GA) has been proposed and investigated to calculate the optimal coefficients of a second order relationship between the flow and the outlet pressure for a PRV to minimize the background leakage. The obtained curve can be subsequently implemented using a flow modulation controller in a feedback control scheme.

The Aquai-Mod® is a hydraulic device to control and modulate the outlet pressure of a PRV according to the valve flow. The controller was experimentally tested to assess its performance and functionality in different conditions and operating ranges. The mathematical model of the controller has been developed and solved, in both steady state and dynamic conditions. The results of the model have been compared with the experimental data and showed a good agreement in the magnitude and trends.

A new method for combined energy and pressure management via integration and coordination of pump scheduling with pressure control aspects has been created. The method is based on formulating and solving an optimisation NLP problem and involves pressure dependent leakage. The cost function of the optimisation problem represents the total cost of water treatment and pumping energy. Developed network scheduling algorithm consists of two stages. The first stage involves solving a continuous problem, where operation of each pump is described by continuous variable. Subsequently, the second stage continuous pump schedules are discretised using heuristic algorithm.

Another area of research has been developing optimal feedback rules using GA to control the operation of pump stations. Each pump station has a rule described by two water levels in a downstream reservoir and a value of pump speed for each tariff period. The lower and upper water switching levels of the downstream reservoir correspond to the pump being “ON” or “OFF”. The achieved similar energy cost per 1 Ml of pumped water. In the considered case study, the optimal feedback rules had advantage of small number of ON/OFF switches, which increase the pump stations lifetime and reduce the maintenance cost as well.

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Table of Contents

List of figures

List of tables

List of variables

Chapter 2

A	Known matrix of coefficients
$\mathbf{b}$	Vectors of (known) coefficients
$\mathbf{c}$	Vectors of (known) coefficients
$f(x)$	Objective function
$\mathbf{x}$	Vector of variables (to be determined),

Chapter 3

A	Hydraulic pump characteristic coefficient
a	Pump efficiency coefficient
B	Hydraulic pump characteristic coefficient
b	Pump efficiency coefficient
C	Hazen-Williams coefficient, dimensionless,
C	Hydraulic pump characteristic coefficient
c	Pump efficiency coefficient
D	Pipe diameter in [m],
d_i	Demand allocated to node i,
$d_i(t_{\mathrm{min}})$	Demand of node i at time t_{min}
e/D	Internal relative roughness of a pipe
f	Darcy friction factor
F	Pump power coefficient
g	Acceleration due to gravity, 9.81 m/s^2.
G	Pump power coefficient
H	Pump power coefficient
H	Node elevation
h	Total head
h_i	Total head at node i
h_j	Total head at node j
hp_l	Head generated by the pump in line l

i	Node index
j	Node index
K	Head loss coefficient
k	Leakage coefficient
L	Pipe length in [m]
l	Pipe index
$l(t)$	Nodal leakage flow at time t
l_i	Leakage flow allocated to node i
l_{loop}	Set of links in the closed loop
l_{path}	Set of links in the path
n	Head loss equation exponent.
n	Number of parallel identical pumps
n	Exponent for the head loss equation
N_i^-	Set of pipes carrying out flow from node i
N_i^+	Set of pipes supplying flow to node i
N_{link}	Number of links
N_{loop}	Number of closed loop
N_{node}	Total number of nodes
N_{ploop}	Number of pseudo-loop
$P(t)$	Nodal pressure at time t
$P_i(t_{\min})$	Pressure of node i at time $t_{\min}$
q	Flow rate in (l/s)
$q(t_{\min})$	Minimum night flow (MNF)
q_l	Flow rate in pipe l
R	Coefficient of head loss equation
Re	Reynolds number
R_l	Loss head coefficient in pipe l
s	Pump speed
t	Time
$t_{\min}$	The time of minimum night flow
u	Average flow velocity in the pipe
W	Pumping power

α	Leakage exponent
β	Constant factor
Δh	Pressure drop due to friction expressed in meter of liquid head
Δq	Correction to flow rates around each loop
η	Pump efficiency
κ	Constant factor depends on the unit used for L, D and q.
ρ	Water density

Chapter 4

$f(x)$	Objective functions
$g_i(x)$	Constraints functions
x	Vector of decision variables (x_1, x_2,…, x_n)
x^*	The values of the decision variables that minimise the objective function
$h(x)$	Equality constraint

Chapter 5

$c_i(t)$	Price per unit of volume including the cost of production, treatment and transport at time t
d_i	Demand allocated to node i
$h_{b,i}$	Head of boundary nodes
$h_{b,i,\max}$	Maximum service head of boundary nodes
$h_{b,i,\min}$	Minimum service head of boundary nodes
$h_{i,\max}$	Maximum service head
$h_{i,\min}$	Minimum service head
$\hat{h}_i(t)$	Optimal time schedules for the PRV set-points
$h_{t,i}$	Head of critical nodes
$h_{t,i,\max}$	Maximum service head of critical nodes
$h_{t,i,\min}$	Minimum service head of critical nodes
H_i	Elevation of node i

h_i	Head in [m] at node i
h_j	Head in [m] at node j
I_b	Set of boundary nodes
$I_{PRV} =$	Set of boundary and internal PRVs
i	Index of origin node
j	Index of destination node
k_i	Leakage coefficient
$K_{ij}(v_{ij})$	Resistance modification coefficient related to the valve opening v_{ij} ,
l_i	Leakage flow allocated to node i.
N_{demand}	Set of nodes have a demand
N_i^-	Set of nodes connected to node i as an origin node
N_i^+	Set of nodes connected to node i as a destination node
q_{ij}	Flow in [l/s] from node i to node j through the element.
R_{ij}	Resistance of either a pipe or a valve element
T	Set of time steps.
$q_{b,i}$	Boundary flow
$q_{b,i,\max}$	Maximum boundary flow
$\hat{q}_i(t)$	PRV optimal flows corresponding to optimal set-points
$q_{i,\max}$	Maximum boundary flow
v_{ij}	Valve opening [%]
α	Leakage exponent
ϕ_t	Total cost of boundary flows, objective function

Chapter 6

A	Coefficient of the optimal flow modulation curve, decision variable
B	Coefficient of the optimal flow modulation curve, decision variable
C	Coefficient of the optimal flow modulation curve, decision variable
$h_i(t)$	PRV outlet head
$h_{i,\max}$	Maximum head limit

$h_{i,\min}$	Minimum head limit
I_c	Set of critical node
$l_i(t)$	Leakage flow at node i
$p_i(t)$	Pressure of the critical node i at time t
p_{min}	Minimum allowed pressure in the system
$q_i(t)$	PRV flow
T	Set of time steps
ϕ	Total cost of boundary flows, fitness function
Θ	Penalty term

Chapter 7

a_1	Areas of the bottom of the moving element of the PRV
A_1	Internal cross sectional areas of the large cylinder of the controller
a_2	Areas of the top of the moving element of the PRV
A_2	Internal cross sectional areas of the small cylinder of the controller
A_4	Internal cross sectional area of the connecting pipe between Pitot tube and T-junction (*t2*)
A_j	Discharge area of the jet
$A_{mv,out}$	Cross sectional area of the PRV outlet
A_{Pitot}	Cross sectional area of the Pitot tube
Cv_{fo}	discharge capacitance of the fixed orifice
Cv_j	Discharge capacitance of the pilot valve
Cv_{ma}	Discharge capacitance of modulation adjuster
Cv_{mv}	Discharge capacitance of the PRV
Cv_{nv}	Discharge capacitance of the bi-directional needle valve
D_4	Diameter of the connecting pipe between Pitot tube and T-junction (*t2*)
f_4	Friction coefficient of the connecting pipe between Pitot tube and T-junction (*t2*)
f_m	Friction coefficient of the moving element of the PRV
f_{sh1}	Friction coefficient of the modulation shaft
f_{sh2}	Friction coefficient of the pilot shaft
g	Gravitational acceleration

h_{cc}	Pressure of control chamber of the controller
h_{cj}	Pressure of jet chamber of the controller
h_{cpt}	Pressure of Pitot chamber of the controller
h_{in}	PRV inlet pressure
h_{out}	PRV outlet pressure
$h_{out,t}$	Total pressure at the PRV outlet
h_{t1}	Pressure of the T-junction (*t1*)
h_{t2}	Pressure of the T-junction (*t2*)
h_{vc}	Pressure of PRV control space
k_{sp1}	Stiffness coefficient of the springs on the modulating shaft
k_{sp2}	Stiffness coefficient of the springs on the pilot shaft
L_4	Length of the connecting pipe between Pitot tube and T-junction (*t2*)
$L_{c1,2}$	Length of the fixed section of the controller
L_{c3}	Length of the variable section of the controller (main pressure adjuster)
L_{sh1}	Length of the modulation shaft
L_{sh2}	Length of the pilot shaft
m_m	Mass of the moving element of the PRV
m_{sh1}	Mass of the modulation shaft
m_{sh2}	Mass of the pilot shaft
n	Number of a valve opening turns
N_{mpadj}	Number of opening turns of the main pressure adjuster
PRV	Pressure reducing valve
q_1	Flow from the PRV inlet to the T-junction (*t1*)
q_2	Flow from the control space of the PRV to T-junction (*t1*)
q_3	Flow from/to the valve control space through bi-directional needle valve
$q_{3,sat}$	Saturation flow of the bi-directional needle valve
q_4	Flow through the Pitot tube
q_5	Flow from/to the Pitot chamber of the controller
q_6	Flow through the modulation adjuster
q_m	Main flow through the PRV
t1	T-junction 1
t2	T-junction 2

x_m	Displacement of the moving element of the PRV
x_r	Gap between the jet and the seat of the pilot valve
x_{sh1}	Displacement of the modulation shaft
x_{sh2}	Displacement of the pilot shaft
Δh,	Pressure loss across the element
β_1	Variable depends on the discharge capacitance of the fixed orifice and the pilot valve
$\beta_{1,\mathrm{critical}}$	Value of β_1 at which the model is singular
β_2	Variable depends on the discharge capacitance of the fixed orifice and the pilot valve
ρ	Density of water

Chapter 8 & 9

a	Vector of lower bounds
b	Vector of upper bounds,
c	Hazen-Williams coefficient
$c^j(k)$	Control variable vector represents the number of pumps ON
$c_{k_c}^j$	Continuous control of pump station j at continuous time step k_c
$\tilde{c}_{k_d}^j$	Discrete control of pump station j at continuous time step k_d
d	Pipe diameter
d_c	Vector of demands
E	Pump mechanical power coefficient
F	Pump mechanical power coefficient
$f_j\left(q^j(k), c^j(k)\right)$	Electrical power consumed by pump station j
$f(x)$	Objective function
G	Pump mechanical power coefficient
$g_i(x)$	Non equality constraint functions
H	Pump mechanical power coefficient
h_{dest}	Heads at the destination node
$h_i(x)$	Equality constraint functions

$h_f(k)$	Water level in reservoir *f* at time *k*
$h_f^{\max}(k)$	Maximum limit of water level in reservoir *f* at time *k*
$h_f^{\min}(k)$	Minimum limit of water level in reservoir *f* at time *k*
h_{orig}	Heads at the node
J_p	Set of indices for pump stations
J_p	Set of pumps
J_s	Set of indices for treatment works
k	Vector of leakage coefficients
k	Time index
k_c	Index of continuous time step
k_d	Index of discrete time step
k_0	First/initial time step of time horizon
k_f	Last/final time step of time horizon
l	Pipe length
l_c	Vector of leakages
$\mathbb{N}$	Integer number
n_c	Number of continuous time steps in one switching period
n_d	Number of discrete time steps in one switching period
P	Penalty value
p	Vector of node pressures
$P(q,u,s)$	Pump mechanical power
q	Pump flow
q	Vector of branch flows
q	Flow through an element.
$q^j(k)$	Flow of pump station *j*
R	The pipe resistance
$\mathbb{R}$	Real number
s	Pump speed
$s^j(k)$	Vector represents pump speed (for variable speed pumps)
$s_{k_c}^j$	Continuous speed of pump station *j* at continuous time step k_c

$\tilde{s}_{k_d}^{j}$	Discrete speed of pump station j at continuous time step k_d
sp_i^j	Switching period number i for pump station j
u	Number of pumps ON
$u_{k_c}^{j}$	Continuous number of pumps being "ON" of pump station j at continuous time step k_c
$\tilde{u}_{k_d}^{j}$	Discrete number of pumps being "ON" of pump station j at continuous time step k_d
x	Vector of decision variable
z	Objective function
α	Leakage exponent
$\Delta h^j(k)$	Delivered head of pump station j
$\delta^j(sp_{i,j})$	Difference between the continuous and discrete flow of pump station j during switching period $sp_{i,j}$
ϕ	Total cost of pumping energy and boundary flows , objective function
ϕ	Specific cost of pumping energy, fitness function
$\phi_{k_c}^{j}$	Total flow through pump station j obtained from continuous schedule
$\phi^j(sp_{i,j})$	Total continuous flow of pump station j during switching period $sp_{i,j}$
$\psi^j(sp_{i,j})\Big\vert_{\text{integer}\left(u_{k_c}^{j}\right)}$	Total discrete flow delivered by $\text{integer}\left(u_{k_c}^{j}\right)$ pumps during a switching period
$\gamma_j^p(k)$	Function represents the electrical tariff
$\gamma_s^p(k)$	Treatment cost
η_{k_d}	Number of discrete schedule periods k_d in a switching period
Λ_c	Node branch incidence matrix
τ_c	Time step for continuous pump schedules
τ_d	Time step for discrete pump schedules
$\bar{\psi}^j\Big\vert_{\text{Additional Pump}}$	Average discrete flow delivered by each additional pump in a discrete time step
$\psi_{k_d}^{j}$	Total flow through pump station j obtained from discrete schedule
$\psi^j(sp_{i,j})$	Total discrete flow of pump station j during switching period $sp_{i,j}$

Abbreviations

ACO	Ant Colony Optimization
ANN	Artificial Neural Network
CNSGA	Controlled Elitist Non Dominated Sorting Genetic Algorithm
DLL	Dynamic Link Library
DMA	District Metered Area
DMZ	District Metering Zone
DNLP	Dynamic Non-Linear Programming
EA	Evolutionary Algorithm
FSP	Fixed Speed Pumps
GA	Genetic Algorithm
GRG	Generalised Gradient Method
LRCs	Lower bounds of reservoirs constraints
MINP	Mixed Integer Nonlinear Programming
Ml/d	Million Litres per Day
MNF	Minimum Night Flow
MO	Multi-Objective
MOEA	Multi-Objective Evolutionary Algorithm
NLP	Non-Linear Programming
NSGA	Non Dominated Sorting Genetic Algorithm
NSGA-II	Non Dominated Sorting Genetic Algorithm- Second Version
ORC	Operational Response Centre
PLCs	Programmable Logic Control
PRV	Pressure Reducing Valve
PS	Pump Station
Re	Reynolds Number
RM	Reduced Model
SCADA	Supervisory Control and Data Acquisition
SCE-UA	Shuffled Complex Evolution-University Of Arizona
SOM	Self-Organized Map
SPEA	Strength Pareto Evolutionary Algorithm
SQP	Sequential Quadratic Programming
SR	Service Reservoir
TWL	Top Water Level
VSP	Variable Speed Pump
WDS	Water Distribution System
WTW	Water Treatment Work

Chapter 1

1 Introduction

1.1 Pressure and Leakage Managements in Water Distribution Systems

Globally, water demand is increasing while the recourses are diminishing. Water loss from water distribution systems (WDSs) has long been a feature of the WDS operations management. Water loss occurs in all WDSs, only the quantity of loss varies and depends on the physical characteristics of the pipe network, operating factors and parameters, and the level of technology and expertise applied to control this loss.

Reducing and controlling water loss is becoming very important issue in this age of rapidly growing demand and relative abundance to one of relative scarcity of the water resources, and climate changes that bring droughts to many locations over the world (Houérou 1996). The water resources are subjected to the fluctuations of the nature and are therefore largely beyond the human control. In order to preserve valuable water resources, many water utilities have been developing new strategies to minimise losses to an economic and acceptable level.

Residential, commercial, industrial, public water use, and unaccounted system loss and leakage constitute the overall water demand. While all components create revenue to the water utility, the unaccounted system loss and leakage are not associated with total cost revenues, and are a source of wasted production costs. With today's high water production, treatment and transmitting costs and rates, the expense of detecting and reducing the unaccounted for water and leakage is an attractive solution for minimizing operating expenditures.

Water distribution networks in all countries around the world encounter water loss, for example, in Addis Ababa, Ethiopia, nearly 50% of the produced water is lost at different levels of the distribution system before reaching the consumers (Desalegn 2005). Also, in City of Mutare, Zimbabwe, unaccounted for water is averaged 57% (Marunga et al. 2006). In many Asian cities non revenue water amounts to 46% of total demand which over 75% are real losses (Rogers 2005). Similar level of losses exists in Turkish cities that have average yearly water loss as high as 50% of the water volume produced

(Çakmakcı et al. 2007; Öztürk et al. 2007). For comparison the Gold Coast City, Australia, an approximately 10% of the potable water is lost through leakage (Girard and Stewart 2007). Figure 1.1 depicts the total leakage in Million litres per day (Ml/d) in UK during the last 15 year, and recently the water utilities implemented leakage and pressure control management policies in order to reduce the leakage. High and increasing water losses are an indicator of ineffective planning and construction, and insufficient low operational and maintenance activities.

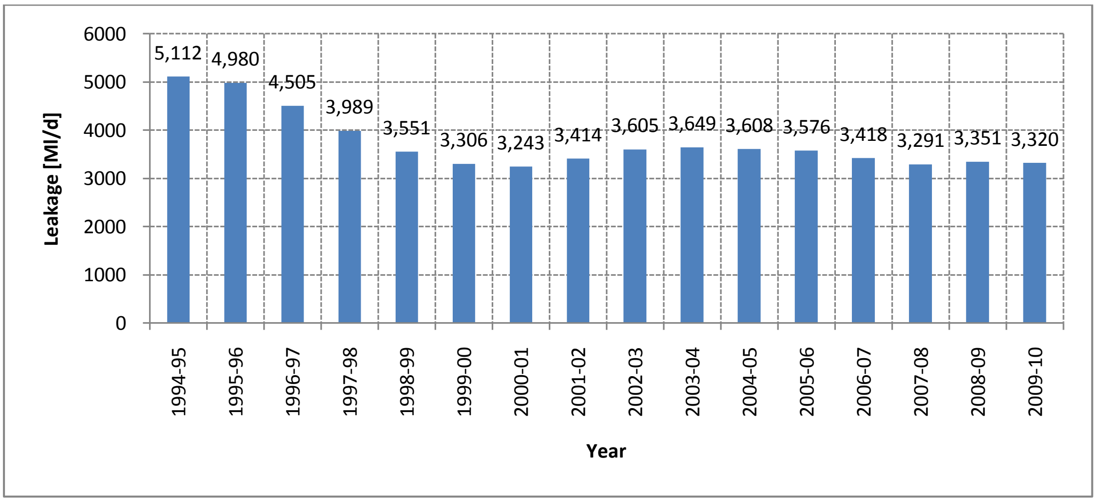


Figure 1.1. Total leakage in UK from 1994 to 2010 (OFWAT 2006, 2008)

It appears that the loss was decreased in the period of 1995 to 2000 from 5112 Ml/d to 3243 Ml/d or by 35%, then increased slowly to 3649 Ml/d in 2003 followed by a slight reduction to 3291 Ml/d in 2007, then kept constant around a value of 3,300 Ml/d in the last 4 years. These values show that more effort is still required to minimize the amount of leakage by using new strategies for pressure and leakage managements.

It is important to distinguish between water loss and water leakage. Water loss is a total loss and equals the real losses and apparent losses from network. Real losses are physical losses and comprise leakage from pipes, joints and fitting, leakage through service reservoir floors and walls as well as from reservoir overflows. Real losses can be severe and can last undetected for long time, months or even years. The quantity of the water loss depends mainly on the network characteristics such as length of mains, number of service connections, length and material of supply pipe, the nature of the soil and infrastructure condition and the operating parameters like pressures and the leak detection and repair policies that are speed of detection, location and repair. Real losses are usually the major part of the water loss. This shows that the real losses in WDSs can be driven down by reducing pressure in the system, improving the speed of detection, location and repair of burst, also by infrastructure improvements. While, apparent losses comprise from pilferage consumption (theft and illegal use) and metering errors. Not all the losses of the WDSs consist of the real and apparent losses only, but also the overuse or misuse of water.

The options available to reduce the leakage are represented diagrammatically in Figure 1.2. This shows that leakage can be reduced by reducing pressure on the system, improving the speed of detection, location and repair of leaks and also by infrastructure improvements. Water companies undertake a mixture of these complimentary actions. General pipe rehabilitation is the most costly and long term action, but is undertaken to improve a number of different factors including leakage and water quality. Operational pressure management is a cost-effective means of reducing leakage over whole sub-networks, and for reducing the risk of further leaks by smoothing pressure variations. Pressure management also has other important benefits in addition to the reduction of existing leakage.

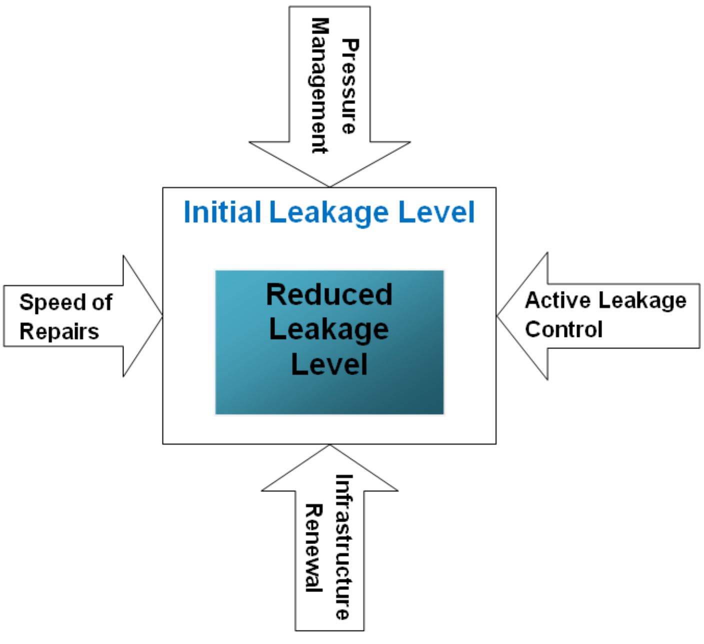


Figure 1.2. Schematic representation of leakage reducing options (Lambert 2000; Thornton and Lambert 2005)

The rates of the real losses from WDSs vary with pressure (Giustolisi et al. 2008), as pressure changes, the leakage area particularly at joints and fittings and on non-metal pipes change. The pressure of surges and high pressures influence the rate at which new leaks occur (Lambert 2000). In order to reduce the leakage levels from WDSs, pressure management is now recognised as one of the most efficient and cost effective policy (AbdelMeguid et al. 2007; AbdelMeguid et al. 2009c; AbdelMeguid et al. 2009d; Chen and Powell 1990; Girard and Stewart 2007; Marunga et al. 2006; Ulanicki et al. 2008a).

Water Utilities design potable WDSs to provide a minimum level of service pressure throughout a day at the critical node in the network. The critical node is generally either the highest point in the system or the point most distant from the source although it may be a combination of the two depending upon local topography and various other factors. Since most systems are designed to provide a minimum pressure throughout the day, they are generally designed to meet this pressure requirement during periods of peak demand when the friction losses are at the highest and inlet pressures are at their lowest. Because of this design methodology, most systems experience higher pressures than necessary during the remaining non-peak demand periods. This is evident from the fact that in most water networks the major burst pipes tend to occur during the late evening and early morning periods when system pressures are at their highest values. Therefore, the pressure in a WDS is considerably higher than required during the most of the time, also, leakage increases with increased pressure, then it can be concluded that leakage levels in most systems are higher than they should be during most of the time. It is clear that the excess pressure in a system can be reduced, then so too can the leakage.

The main objective of pressure management is to minimise the excess pressure in a WDS, which in turn will reduce leakage as well as the frequency of burst pipes. Significant savings can often be made and there are many examples where pressure management has been extremely successful (Çakmakcı et al. 2007; Desalegn 2005; Girard and Stewart 2007; Marunga et al. 2006; Rogers 2005; Yates and MacDonald 2007). With the aid of pressure reducing valve (PRV) and the recent electronic and hydraulic controllers, it is now possible to apply the pressure management policies that can reduce the leakage to its possible minimum value.

Pressure management is usually implemented across areas that are typically supplied through PRVs and closed at all other boundaries, and known as districted metered areas

(DMAs) (Alonso et al. 2000; Prescott et al. 2005; Ulanicki et al. 2000). Single-feed PRV schemes are often adopted for ease of control and monitoring but risk supply interruption in the event of failure. Multi-feed systems improve the security of supply but are more complex and incur the risk of PRV interaction leading to instability (Prescott and Ulanicki 2004; Ulanicki et al. 2000).

Pressure management is more efficient if there is a possibility of automatically adjusting the set-points of a PRV (The PRV outlet pressure) according to the PRV flow - so called flow modulation. The PRV set-point can be adjusted electronically or hydraulically. The former require the use of a flow sensor, a microcontroller and solenoid valves acting as actuators. The major disadvantages of this solution are the necessity of providing power supply and the exposure of the electronic equipment to harsh field conditions. A hydraulic flow modulator is a much simpler and robust solution.

The AQUAI-MOD® hydraulic controller manufactured by the Aquavent company (Peterborough, UK) is probably the first hydraulic flow modulator available on the market. The AQUAI-MOD® hydraulic controller can be used to implement optimal pressure control strategies by modulating the outlet pressure of the PRVs according to the flow. This will minimise continuous over pressurisation of the mains and therefore reduce stress on the mains causing potential leaks.

During implementation of a pressure control scheme, both steady state and dynamic aspects should be considered (Brunone and Morelli 1999; Prescott and Ulanicki 2003; Prescott and Ulanicki 2008; Ulanicki et al. 2000). The steady state aspects ensure that PRV set-points are changed according to the demand to minimise background leakage and to satisfy the minimum required pressure at the critical nodes. The dynamic aspect considers preventing excessive pressure hunting (oscillations) across a network caused by interactions between modulating valves and dynamics in water networks. A better understanding of the dynamics of PRVs and networks will lead to improve control strategies and reduce both instabilities and leakage.

Supervisory pressure control schemes cover wide areas, and has a crucial role to play in background leakage reduction, burst reduction and quality of supply; stabilising pressure for customers; reducing the demand for energy and reducing overall water supply costs (Cembrano et al. 2000).

Water utilities use pressure management to reduce background leakage and the incidence of pipe bursts and to extends infrastructure life (Thornton and Lambert 2007). Furthermore, the pressure management is considered jointly with energy management because both problems are interlinked, hence pressure management-reduces leakage and subsequently reduces energy consumption by reducing the pumped volume of water and therefore reduces unnecessary energy costs (Colombo and Karney 2002, 2009).

1.2 Energy Management in Water Distribution Systems

The water utilities have started to investigate the integration of on-line telemetry and optimal control systems in an effort to reduce the operating costs. Supplying water can consume large amounts of electricity, which generally constitute the largest expenditure for nearly all water utilities worldwide. These energy costs depend on the energy usage and the energy rate. Energy rates are often structured to promote off-peak energy usage with lower rates and penalize peak period with higher rates. Energy-saving measures in WDSs can be realized in different ways, from field-testing and proper maintenance of equipment to the use of optimal control. Energy usage can be reduced by decreasing the volume of water pumps, lowering the head against which it is pumped, or reducing the price of energy, and increasing the efficiency of pumps. Utilities can further reduce energy costs by implementing on-line telemetry and control systems, and by managing their energy consumption more effectively and improving overall operations using optimized pumping operations and reservoir control. One of the greatest potential areas for energy cost-savings is the scheduling of daily pump operations. Scheduling of WDS operation is a complex task, and consisting of applying cost saving measures whilst aiming to satisfy various constraints on the system. The most significant savings may be made by concentrating the highest power pumping during the night, when electricity is least expensive, and running the variable speed pumps at its maximum efficiency. This leads to filling the reservoirs over the night, which can be emptied during the day, thus reducing the amount of pumping required meeting consumer demand. Typical constraints, which should be considered in the optimisation problem include choosing proper pumps that have sufficient driving head to overcome hydraulic losses and supply user demand, keeping reservoir levels within set bounds to avoid the danger of overflow, and at the same time to maintain security of supply, keeping mains pressures below certain levels to reduce leakage and the risk of pipe burst, finally, maintaining water quality above the maximum admissible concentration levels.

There have been several attempts in recent years to develop optimal control algorithms to optimise the operation of WDSs. Many algorithms were oriented towards determining the optimum pump scheduling policies to achieve the minimum operating cost, and were based on the use of linear programming, nonlinear programming, dynamic programming, enumeration techniques, and general heuristics. However, the success of these algorithms and methods has been very limited and very few have actually been applied to real WDS.

Optimisation techniques in engineering practice have a limited acceptance, due to the complexity of such techniques. In addition, these techniques are highly dependent upon the number of pumps and reservoirs being considered. They are generally subject to over simplification of the network model and its components, and they may be trapped at local optima and not lead to a global optimal solution.

1.3 Combined Energy and Pressure Management in WDSs

WDSs lose a considerable amount of potable water from their networks due to leakage, whilst using a significant amount of energy for water treatment and pumping.

Optimisation of energy consumption, pressure management, and leakage control has often been considered separately, without taking into account interactions (synergy) or the integration, which has been introduced and tested in this study. A significant energy saving can be accomplished by matching pumping schedules with time varying electricity tariffs, considering the network hydraulics and the available storage in the system. However, little has been done to co-ordinate energy management and pressure management operations. Often the pump stations are oversized and provide excess pressure (energy) which is subsequently throttled by valve operations. There is an obvious opportunity for further saving and extension of the life of underground infrastructure by refining control of pumps.

The objective of applying energy and pressure managements in water supply systems can be defined as, “supply demands at minimum cost while satisfying operational constraints”. The principal costs involved are usually electricity charges for pumping, treatment costs and charges for imported water. This objective can be achieved by reducing the leakage in the mains (pressure control aspect) and minimising the electric power consumption by the pump stations (optimal pump scheduling aspect). Reduction of leakage, hence savings of clean water, can be achieved by introducing pressure control algorithms (Ulanicki et al. 2008a; Ulanicki et al. 2000). Reducing electricity cost by pump stations can be achieved by increasing electrical efficiency of the drivers and the frequency converters and the mechanical efficiency of the pumps, scheduling of pumps so that they operate during off-peak period (cheap electricity tariff) and close to the best efficiency point, and reducing the volume of pumped water by minimizing the background leakage.

In order to integrate the optimisation of pump schedules and the optimal pressure control, if the PRV inlet pressure is higher than required it could be reduced by adjusting pumping schedules in the upstream part of the network, in the cases when this is possible (i.e. when there is not an intermediate distribution reservoir at the upstream side). Modern pumps are often equipped with variable speed drives, therefore, the pressure could be controlled by manipulating pump speed, thus reduce leakage and energy use. The proposed approach is an extension of the pump scheduling algorithms described in (Bounds et al. 2006), and based on nonlinear programming (NLP) and novel local search approach supported by heuristics derived from numerous industrial case studies. The developed algorithm includes the simplified models of the network (Ulanicki et al. 1996) to reduce the calculation time and improve robustness of the algorithms in order to satisfy real-time requirements. The module calculates time schedules for treatment works, pumps, valves, and reservoirs. Furthermore, taking into account the presence of pressure-dependent leakage whilst optimising pumps operation influence the obtained schedules. It can allow control rules to be derived for the transmission system by running different hypothetical scenarios and synthesising these rules. Original contribution presented in this thesis to knowledge is creating a new methodology for combined energy and pressure management.

1.4 Aims and objectives

The presented work aims to develop a novel approach and practical tools for pressure, leakage and energy management in order to improve customer service and efficiency of WDSs. Pressure, leakage and energy management is an essential component of a strategy to improve customer service and to reduce energy usage and water losses. The presented work addresses the key aspects of pressure and energy management and optimal operation of pump stations in WDSs.

The main objective of energy and pressure managements in water supply systems is to minimise the operating cost in terms of electricity charges for pumping, treatment costs and charges for imported water in terms of background leakage reduction, while satisfying operational constraints. The overall aim is to improve pressure and leakage control and energy management in WDSs considering the latest control technologies of PRV and variable speed drives for pumps.

1.4.1 Objectives

- To develop innovation in pressure management to deliver key leakage and energy savings
- To improve dynamic behaviour of DMAs under control of PRVs
- To provide options to make significant savings in energy e.g. through pump schedule optimisation
- To develop a tool facilitating the on-line and off-line energy and pressure management in the grid part and in the distribution part of the water system.
-

1.5 Work published

Many scientific international peer journal and conference papers have been published from the material of the current study. As well, a number of technical reports have been written as deliverables to NEPTUNE project (Morley et al. 2009; Savić et al. 2008) under different work packages. The published work and technical reports are listed in section “Bibliography”.

1.6 Structure of the thesis

The thesis is presented in 10 chapters including an extensive literature review, description of new algorithms for pressure control, description and testing of embedded local hydraulic controller for a PRV and energy managements and application of the algorithms off-line and online to different case studies before concluding with a summary of the overall results. The individual content of each chapter is given in the following paragraphs.

- Chapter 1, "Introduction"

  In the current chapter, a general introduction for pressure and leakage control and energy management in WDS is presented, followed by the motivations, aims and objectives of the current study also the used methodologies to achieve these objectives.

- Chapter 2, "Literature review"

  Chapter 2 presents a comprehensive review of the state of the art of the two main problems researched in this thesis, pressure and leakage control, and energy management in WDSs. The chapter is split in two sections discussing the scientific progress made in the disciplines of pressure and leakage control, and energy management in WDSs, respectively. Each section looks at different algorithms that have been applied to either problem, and how the individual approach has contributed to knowledge in the respective field.

- Chapter 3, "Management and Control Schemes of Water Supply and Distribution Systems"

  In chapter 3, a brief review of operational control and decision structures for WDSs has been conducted. In addition, descriptions of behavioural equations for modelling water network components that have been used in the current study are presented.

- Chapter 4, "Overview of the Optimization Methods Used in This "

  In chapter 4, a global definition of the optimization problem followed by a brief study of the optimization methods and solvers that have been used within this study.

- Chapter 5, "Pressure and Leakage Management in Water Distribution "

  In chapter 5, a fast and efficient method to calculate the optimal time schedules and flow modulation curves is presented. The time modulation methodology is based on solving a NLP problem with equality constraints represented by a hydraulic model with pressure dependent leakage term and inequality constraints representing operational requirements. The cost of boundary flows which include leakage flows has been minimized. Evaluation of optimal control strategies and benefit analysis in terms of leakage reduction for the two case studies provided by Yorkshire Water Services has been included.

The findings of this chapter have been published in (AbdelMeguid et al. 2007; AbdelMeguid et al. 2009c; AbdelMeguid et al. 2009d; Ulanicki et al. 2008a).

- Chapter 6, "Pressure and Leakage Management in WDSs via Flow Modulation PRVs"

  In chapter 6, a GA has been used to calculate the coefficients of second order relationship between the flow and the optimal outlet pressure for a PRV. The method has been implemented in Matlab linked to the Epanet hydraulic simulator. The obtained curve can be subsequently implemented using a flow modulation controller (Chapter 7).

  The findings of this chapter have been published in (AbdelMeguid and Ulanicki 2010b)

- Chapter 7, "Embedded Hydraulic Controller for Pressure Reducing Valve"

  Chapter 7 describes a development of mathematical models, which represent static and dynamic properties of the AQUAI-MOD® hydraulic controller coupled with a standard PRV as well as a new experimental setup for testing the controller, for calibrating and validating the controller models. The purpose of the AQUAI-MOD® controller is to modulate the PRV outlet pressure according to the valve flow.

  The findings of this chapter have been published in (AbdelMeguid et al. 2008, 2009b, 2010)

- Chapter 8, "Combined Pressure, Leakage and Energy Management in Water Distribution "

  In this chapter, combined algorithm for pump scheduling for energy management and DMA pressure control for leakage reduction is presented. The proposed approach is based on NLP and novel local search ideas supported by heuristics derived from numerous industrial case studies. The module calculates time schedules for treatment works, pumps, valves and reservoirs.

  The findings of this chapter have been published in (AbdelMeguid et al. 2009a; Skworcow et al. 2009a; Skworcow et al. 2009b; Skworcow et al. 2009c; Skworcow et al. 2010)

- Chapter 9, "Feedback Rules for Operation of Pumps in a Water Supply "

  In this chapter, a novel approach of optimising the operation of pumps stations in WDS based on optimal feedback rules has been investigated. Operating and controlling the pump stations via optimal feedback rules aims to minimize the energy consumptions, and provides a robust control policy. The optimal feedback rules have been derived using GA.

The findings of this chapter have been published in (AbdelMeguid and Ulanicki 2010a)

- Chapter 10, "Conclusion and Future "

  The thesis is concluded by the overall summary of the all finding from this study, conclusion and the proposed future work.

In addition, four appendices are attached at the end of the dissertation to provide more details and explanations for different parts, these appendices are

- Appendix A

  Brief descriptions of GAMS code, CONOPT 3 and software implementation

- Appendix B

  In this appendix, detailed information about the network of Oldham water supply system is provided. In addition, a model description and simplification are also discussed. As well, the original contribution to the knowledge is summarized.

- Appendix C

  The effect of changing the lower bounds of reservoirs constraints on the continuous solution

- Appendix D

  Descriptions of the files on the enclosed CD

Chapter 2

2 Literature review

This chapter gives a comprehensive overview of the state of the art of the two main problems considered in this thesis, pressure and leakage control, and energy management in WDSs. The chapter is split in two sections discussing the scientific progress made in the disciplines of pressure and leakage management, and energy management in WDSs, respectively. Each section looks at the different algorithms that have been applied to either problem, and how the individual approach has contributed to knowledge in the respective field. Judgement is based on the achieved final solution of the specific algorithm (in terms of accuracy, applicability, necessary model simplifications, and computational efficiency) and how it helped or inspired other scientist to develop on their original idea.

2.1 Pressure and Leakage Management in WDSs

Water companies have tried many management strategies, which are general pipe rehabilitation, direct detection and repair of existing leaks, and operational pressure management. General pipe rehabilitation is the most costly and long term action, but is undertaken to improve a number of different factors including leakage and water quality (Clark et al. 2002; Engelhardt et al. 2000). Direct detection and repair of existing bursts is one of the most powerful policies, that is used to prevent the high level leakage from burst. Detecting and reducing burst is an attractive solution, and many algorithms have been developed to predict and detect the location and quantify the leakage in WDSs (Koppel et al. 2007; Mounce et al. 2003; Wu and Sage 2006). Operational pressure management is a cost-effective method for leakage reduction over entire DMAs, and for minimizing the risk of further leaks by smoothing pressure variations. Many researchers have presented, developed, and implemented various methods and algorithms to optimise the operational pressure, and the results showed that, the leakage can be reduced by up to 60%. Burn et al. (2002) analysed the effect of employing pressure management techniques on the operating cost of WDSs, which increases the savings by a 20-55%. Girard and Stewart (2007) described implementation of the pressure and leakage management strategies on the Gold Coast, Australia, and the results revealed a good opportunity to achieve significant water savings. Marunga et al. (2006) implemented a pressure management as a leakage reduction, in Mutare, Zimbabwe. The results showed that an operating pressure reduction from 77 m to 50 m resulted in 25% reduction in the total leakage.

2.1.1 Linearization methods

Miyaoka and Funabashi (1984) introduced a modelling technique and an optimal control scheme for water distribution networks. To overcome the large scale and nonlinearity of the network, a network aggregation method and a two-level control scheme were developed. The first level of the scheme decided operating points using a nonlinear optimization method, where the pressure/flow equations were solved using a high-speed technique derived from network flow theory. The second level was a feedback control around the operating points, which absorbed estimate error and small variations in consumption.

Sterling and Bargiela (1984) considered the problem of minimisation of leakages due to over pressurisation in a water distribution network , and presented an algorithm for computation of the optimal valve controls based on the sparse revised simplex method. To cope with the non-linearity of the system a method of iterative linearization based on the Newton-Raphson process was used. Simulation results indicated a potential for 20% reduction of the volume of leakages using optimised valve control.

Jowitt and Xu (1990) described a successive linearization of the nonlinear network equations using the linear theory method. The resultant linear system allows linear programming techniques to minimize the leakage by determining the optimal setting of control valves. The numerical results exhibited that the overall reduction in leakage was about 20%.

Chen and Powell (1990) presented an algorithm to calculate the optimal valve settings in order to reduce leakages in a water network. The optimisation problem was linearised using the method of the least absolute values estimation. Based on state estimation for online monitoring of water networks, the formulation of the optimization problem lead to a linear programming problem. For such a problem, the sparse revised simplex method was employed, which showed effectiveness in speeding up solution time and enhancing numerical stability.

Germanopoulos (1995) integrated the linear theory method into a linear programming technique for the excess pressure minimisation problem taking into account the pressure dependent leakage term. The linear theory method was used in the iterative linearisation of the nodal flow continuity constraints. The resulting linear program was solved at each iteration until convergence to an optimal solution.

2.1.2 Nonlinear Programming

Vairavamoorthy and Lumbers (1998) and Alonso et al. (2000) developed an optimization method to minimize the leakage in WDSs through the most effective settings of flow reduction valves included of pressure-dependent leakage terms in network analysis. The valve setting optimization problem was formulated as a NLP problem and was solved using a sequential quadratic programming (SQP) method.

Ulanicki et al. (2000) investigated a method for planning and implementation of on-line control strategies of predictive and feedback control for areas with many PRVs and many target points. The considered methods explicitly take into account a leakage model. The optimisation of PRV outlet pressure was expressed in the form of non-linear programming problem, and was solved using a solver called CONOPT based on the generalised reduced gradient method (GRG).

2.1.3 Evolutionary Computing and Genetic Algorithms

Savic and Walters (1994) presented a methodology for pressure regulation in a water distribution network encompassing the principles of evolutionary design and GAs. The optimisation problem of minimising the pressure heads was formulated with the settings of isolating valves as decision variables and minimum allowable pressures as constraints. The algorithm developed incorporates a steady-state network analysis model based on the linear theory method.

Araujo et al. (2006; 2003) developed a model with the capacity to support decisions regarding the quantification, localisation and opening adjustment of valves in a network system with the objective to minimise pressures and consequently water losses. Two operational modules were established: the first for the evaluation of an objective function to optimise the localisation of valves in the network system, and the second for the opening valve adjustment in order to optimise pressures through the evaluation of an aptitude function.

Awad et al. (2003) addressed the problem of appropriate electrical motor valves setting for the pressure regulation of a water distribution networks for specified nodal demands by using both GA and a concept known as Shuffled Complex Evolution-University of Arizona (SCE-UA). The comparison of the results from both algorithms showed the superiority of SCE-UA technique to reach the optimal solution using fewer function evaluations than GAs. Awad et al. (2005) presented another technique for improving the existing optimal pressure regulation and leakage minimization algorithms for supervisory water distribution networks. Self-Organized Map (SOM) and an unsupervised Artificial Neural Network (ANN) were trained with the assistance of Supervisory Control and Data Acquisition (SCADA) to classify well regulated pressure cases for the water distribution network based on its actual values of flow meter readings which reflect the real network water demands or consumption. After training the SOM, a simulation step was used to classify the unregulated pressure cases into the different model classes. Based on the classifications the appropriate electrical motor valves setting of the well pressure regulation events were used for the unregulated ones. Using SOM as a pre-optimization method could prevent all errors resulting from applying optimization models, save its computational time and provide an on-line pressure regulation method. The computational results showed the effectiveness of using SOM as a pre-optimization tool for regulating 74% of events within the target pressure range. Awad et al. (2009) described a practical methodology for optimal pressure regulation in water distribution networks. The methodology could be used to design DMAs by employing PRVs to reduce excessive outlet hydraulic pressure at certain times of the day. The proposed method used GA to identify the optimal DMA boundaries and to determine the optimal type, location and setting of the PRVs. The developed optimization algorithms used both fixed and time modulated PRVs. The objective functions estimated benefits of reducing pressure on leakage, pipe burst frequency, pressure-sensitive water consumption, active leakage control effort, and energy consumption and customer contacts.

Nicolini and Zovatto (2009) addressed the problem of optimal pressure management in WDSs through the introduction and regulation of PRVs. The determination of the number, location, and setting of such valves was formulated as a two criteria optimization problem and was solved with multi-objective GAs. The one criterion corresponded to minimisation of the number of valves, and the second was to the minimization of the total leakage in the system, when maintaining the required pressure at all nodes in the system.

2.2 Energy Management in WDSs

In this section, a review of the state of the art of optimal control algorithms for water-supply pumping systems is presented. This is preceded by an overview of the components of a typical control system. Potential control algorithms are then examined and categorized based on their applicability to systems of differing characteristics.

Ormsbee and Lansey (1994) reviewed the existing optimal control methodologies for water-supply pumping systems, and classified methodologies on the basis of the type of system to which the methodology can be applied (single source-single tank or multiple source-multiple tank), the type of hydraulic model used (mass balance, regression, or hydraulic simulation), the type of demand model used (distributed or proportional), the type of optimization method used (linear programming, dynamic programming, or nonlinear programming), and the nature of the resulting control policy (implicit or explicit). Advantages and disadvantages of each approach were presented, along with recommendations for future work. The applicability of technology to an existing water supply pumping system was examined in light of existing technical limitations and operator acceptance issues.

2.2.1 Linear programming method

Linear programming is a technique for the optimization of a linear objective function, subject to linear equality and inequality constraints. Given a polytope and a real-valued affine function defined on this polytope, a linear programming method will find a point on the polytope where this function has the smallest (or largest) value, by searching through the polytope vertices. Linear programs are problems that can be expressed in canonical form:

$$\begin{aligned}&\text{Minimize (or Maximize)}: \mathbf{c}^{\mathrm{T}}\mathbf{x}\\&\text{Subject to}: A\mathbf{x} \leq \mathbf{b}.\end{aligned}$$

where **x** represents the vector of variables (to be determined), **c** and **b** are vectors of (known) coefficients and A is a (known) matrix of coefficients. The expression to be maximized or minimized is called the objective function ($\mathbf{c}^T\mathbf{x}$ in this case). The equations $A\mathbf{x} \le \mathbf{b}$ are the constraints which specify a convex polytope over which the objective function is to be optimized. Linear programming can be applied to various fields of study. It is used most extensively in business and economics, but can also be utilized for engineering problems. Jowitt and Germanopoulos (1992) presented a method based on linear programming for determining an optimal schedule of pumping. Both peak and peak-off electricity charges were considered, as well as the relative efficiencies of the available pumps, the structure of the electricity tariff, the consumer-demand profile, and the hydraulic characteristics and operational constraints of the network were taken into account. The extended period simulation of the network operation to linearise network equations and constraints was used. An application of the method to a real network showed that considerable savings were possible.

2.2.2 Nonlinear programming method

NLP is the process of solving a system of equalities and inequalities constraints over a set of unknown real variables, along with an objective function to be maximized or minimized, where some of the constraints or the objective function are nonlinear.

$$\text{Minimize (or Maximize)} : f(x),\ x \in X$$

where

$$f : R^n \to R$$
$$X \subseteq R^n$$

If the objective function $f(x)$ is linear and the constrained space is a polytope, the problem is a linear programming problem. If the objective function is concave (maximization problem), or convex (minimization problem) and the constraint set is convex, then the program is called convex and general methods from convex optimization can be used. Brion and Mays (1991) presented a methodology based on solving a large-scale NLP problem for the optimal operation of pumping stations in WDSs. Several approximations were made in developing the model. The problem was cast into one that deals primarily with continuous variables; the decision variables were pumping times within pre-specified time periods that have a maximum value equal to the length of the time period and a minimum value of zero. Another assumption was that the decision to turn pumps “ON” can only be made at the beginning of each time period. These limitations could be offset by the use of smaller intervals of time, but at the expense of longer computation times. The model results were computationally reasonable. Global optimality could not be guaranteed. However, multiple local or near-optimal solutions could be obtained from the model. Sakarya and Mays (2000) developed a methodology for determining the optimal operation of pumps with water quality considerations. The methodology was based on describing the operation as a discrete time optimal scheduling problem, and solved by a mathematical programming approach resulting in a large-scale NLP problem. The solution of the optimization problem was obtained by interfacing a hydraulic and water quality simulation code with a nonlinear optimization code. Bound constraints on the state variables were incorporated into the objective function using the augmented Lagrangian penalty method. Three objective functions were used in the model to minimize the deviations of actual substance concentrations from desired concentration values; the total pump duration times; or the total energy cost. The proposed solution methodology could result in a very short operating time during one time interval or may cause the pumps to be switched ON and OFF excessively, which could not be followed for practical purposes. Klempous et al. (1988; 1997) investigated methods and algorithms for operative and dynamical control of pumping stations in WDSs. A multilevel approach based on the idea of aggregation of the pipelines network was proposed. The algorithm of the optimization had two levels. At the upper level, a dynamic problem was solved. Its result was a schedule of the exploitation of reservoirs. The data about flows to the reservoirs were passed to the lower level, where a static problem was solved. Its solution gave the number of pumps turned ON in the pumping station and their current yields. The optimization model consisted of a linear objective function and quadratic constraints. The proposed methodology was not applicable for a medium or large system, for such systems model reduction methods should be used to simplify and reduce the problem dimension. Bounds et al. (2006) and Ulanicki et al. (2007) introduced a similar approach and developed a new dynamic optimization approach to solve large scale optimal scheduling problems for WDSs. The proposed method progressed in two stages, initially a relaxed continuous problem was solved and in the second stage, a mixed-integer solution was found which tracked the optimal reservoir trajectories by time decomposition and application of a local branch and bound method to discretise the relaxed continuous optimal schedule that allowed the operation of fraction of pump. The same methodology was used in Skworcow et al. (2009b; 2009c), but the second stage was replaced by a simple and more robust discretizer. The developed discretizer tracks the continuous pump control followed by manual adjustment based on the continuous and discrete flows. The both methodologies were tested on different case studies and the results showed considerable savings in energy consumptions and pumping cost. Walenda et al. (2006) proposed a novel idea of a feedback control of a WDS taking into account the time dependent electrical tariff. The approach was based on a decision surface concept. The decision surface was constructed using a bundle of optimal trajectories, obtained by solving the open loop scheduling problem for different initial reservoir levels. The decision surface was approximated locally during real time control by a convex polytope.

2.2.3 Dynamic programming

Dynamic programming is a method of solving complex problems by breaking them down into simpler steps and backtracking. It is applicable to problems that exhibit the properties of overlapping sub-problems in a recursive manner. Lansey and Awumah (1994) presented a methodology for determining optimal pump operation schedules for short planning period based on the dynamic programming optimization. A two-level approach was adopted whereby the system hydraulics were analyzed in an off-line mode to generate simplified hydraulic and cost functions for an on-line model. These functions developed for each pump combination allow for rapid evaluation within a dynamic programming optimization algorithm. The applicability of the model was limited by the number of pumps in the system, and was only applicable to small to midsize systems.

2.2.4 Evolutionary Computing

Evolutionary computation is a subfield of artificial intelligence that involves combinatorial optimization problems. Evolutionary computation uses iterative progress, such as growth or development in a population. Evolutionary algorithm (EA) is a subset of evolutionary computation, a generic population-based metaheuristic optimization algorithm.

Evolutionary techniques mostly involve metaheuristic optimization algorithms such as:

- Evolutionary algorithms (comprising genetic algorithms, evolutionary programming, evolution strategy and genetic programming)
- Swarm intelligence (comprising ant colony optimization and particle swarm optimization)

Evolutionary computation have been employed to solve the optimization problem of design and operation of water systems, a review of these methods and its application for optimal pump schedule is presented in the following sections.

2.2.5 Genetic Algorithms (GA) and Multi-objective Evolutionary Algorithms (MOEA)

During the last two decades, the water resources planning and management profession has seen a dramatic increase in the development and application of various types of evolutionary algorithms (EAs). This observation is especially true for application of GAs, arguably the most popular of the several types of EAs that repeatedly prove to be flexible and powerful tools in solving an array of complex problems for water systems. Nicklow et al. (2010) provided a comprehensive review of state-of-the-art of EA methods and their applications in the field of water systems. A primary goal was to identify in an organized fashion some of the seminal contributions of EAs in the areas of WDSs, urban drainage and sewer systems, water supply and wastewater treatment, hydrologic and fluvial modelling, groundwater systems, and parameter identification. Evolutionary computation will continue to evolve in the future as the researcher in water systems encounter increased problem complexities and uncertainty and as the societal pressure for more innovative and efficient solutions rises.

Beckwith and Wong (1995) developed a method for scheduling pumps in WDSs using a GA approach. The objective of the scheduling problem was to ensure that the pumps adequately provide the volume of required water to the WDS, whilst minimising the operational cost. The algorithm took into account the characteristic curves, the efficiency curves, and the flow limits of pumps in the system and the system characteristic curves. The method showed the ability to determine the optimum or near-optimum pump schedule. The repeatability of the method and the computational requirement were high and some work needs to be performed to improve the method so that the computational requirement could be reduced. Mackle et al. (1995) applied a simple GA to discrete scheduling of multiple pumping units in a water supply system with the objective of minimising the overall cost of the pumping operation based over 24 hr, taking the advantage of storage capacity in the system and the availability of off peak electricity tariffs. The results showed that the method was easy to apply and had produced encouraging preliminary results. Several improvements of the single objective GA introduced by Savic et al. (1997). They also investigated MOGA for solving the pump scheduling problem, and implemented MOGA combined with a local search method to increase the GA exploitation features. The aim of the multi-objective approach was to find a spread of good, trade-off solutions with respect to all objectives. Moreover, to improved GA, two different local search strategies based on two different definitions of the neighbourhood of a binary string representing a pump schedule were investigated. The main objective was to minimise the pump operating cost considered pump switching as an additional objective, as well introducing the feasibility of solutions as an additional objective with the highest priority. The model was applied for a system of four fixed speed pump and over 24 hr. Sotelo et al. (2002) tested the applicability and the performance of different evolutionary algorithms, six recognised MOEAs were applied to solve the optimal pump-scheduling problem. The six algorithms were Strength Pareto Evolutionary Algorithm (SPEA), the Non Dominated Sorting Genetic Algorithm (NSGA), its second version (NSGA-II), the Controlled Elitist Non Dominated Sorting Genetic Algorithm (CNSGA), the Niched Pareto Genetic Algorithm (NPGA) and the Multiple Objective Genetic Algorithm (MOGA). In order to satisfy hydraulic and technical restrictions, a heuristic algorithm was developed and combined with the above algorithms. Multi-objective optimisation metrics were used to compare the performance of MOEAs. Experimental results show that SPEA was the best method for this problem, although other algorithms could also be useful. Furthermore, SPEA's set of solutions provided pumping station engineers with many optimal pump schedules to choose from. Engineer's criteria could then be used to make a final selection, knowing other compromise alternatives. Barán et al. (2005) used the six different MOEAs stated earlier to solve an optimal pump-scheduling problem with four objectives to be minimized: electric energy cost, maintenance cost, maximum power peak, and level variation in a reservoir. The six different MOEAs were implemented and compared. In order to consider hydraulic and technical constraints, a heuristic algorithm was developed and combined with each implemented MOEA. Evaluation of experimental results of a set of metrics showed that the Strength Pareto Evolutionary Algorithm achieved better overall performance than other MOEAs for the parameters considered in the test problem, providing a wide range of optimal pump schedules to chose from. A different approach of using parallel and sequential versions of different evolutionary algorithms for multi-objective optimization was used by Lücken et al. (2004) as a tool to aid in solving an optimal pump-scheduling problem, considering four objectives to be minimized: electric energy cost, maintenance cost, maximum power peak, and level variation in a reservoir. López-Ibáñez et al. (2005a, b) considered the pump scheduling problem using a multi-objective (Strength Pareto Evolutionary Algorithm) approach and showed its viability for solving such an optimization problem. Minimizing the pumping energy cost and the number of switching were considered the objectives of the problem. The results were presented in the form of Pareto-optimal solutions, which allows the system operator to examine a range of the solutions and choose one solution with regard to additional criteria. Gogos et al. (2005) considered variety of constraints and objectives while solving optimal pump schedule such as the constraints to maintain strategic security and reliability limits for each water reservoir, and presented a mathematical model and a solution for the pump scheduling problem based on GAs. The main objective was the reduction of the pumping costs. The quality and usability need to be evaluated and enhanced. Wang et al. (2009) proposed a GA-based pump scheduling method for cost reduction and environment protection. The proposed method could achieve lower pumping cost and provide a wider range of eco-aware schedules.

Rao and Salomons (2007) presented an approach for the real-time, near-optimal control of WDSs based on the combined use of an artificial neural network for predicting the consequences of different control settings and a GA for selecting the best combination. By this means, it was possible to find the optimal, or at least near-optimal, pump and valve settings for the present time-step as well as those up to a selected operating horizon, taking account of the short-term demand fluctuations, the electricity tariff structure, and operational constraints. Having grounded any discrepancies between the previously predicted and measured storage levels at the next update of the monitoring facilities, the whole process was repeated on a rolling basis and a new operating strategy was computed. Shamir and Salomons (2008) demonstrated another method to improve the performance of GA for near-optimal real-time on-line operation of urban WDSs. The methodology used a reduced model (RM) of the network, which reproduces its performance over time with high fidelity with optimization by a GA. The RM-GA software used network data, forecasted demands for an operational planning time-horizon (24 h ahead), field data on the current status of the network, time-of-day energy cost data, and operator-imposed constraints on tank water levels and demand junctions pressures. The GA was used to look for the near-least-cost operation plan for the whole time horizon, using the reduced network model. At the end of the hour, the status of the network was updated from field data, the time horizon was rolled ahead by 1 hr, and the process repeated. Experiments were conducted, and energy cost savings of 8% and 10% were obtained for a summer and winter, respectively.

2.2.6 Ant colony optimization

Ant colony optimization algorithm (ACO) is a probabilistic technique for solving computational problems which can be reduced to finding good paths through graphs. This algorithm constitutes some meta-heuristic optimizations. The first algorithm was aiming to search for an optimal path in a graph, based on the behaviour of ants seeking a path between their colony and a source of food. The original idea has since diversified to solve a wider class of numerical problems, and as a result, several problems have emerged, drawing on various aspects of the behaviour of ants. ACO was introduced and applied to design and operations of WDS in (Maier et al. 2003; Zecchin et al. 2007; Zecchin et al. 2005). López-Ibáñez et al. (2007) applied Max-Min Ant System to solve the pump scheduling problem. Instead of the typical binary representation, a representation based on time-controlled triggers was used. The approach was compared to results obtained by a Hybrid GA on the same instance and for the same number of function evaluations. The results obtained by Max-Min Ant System were similar to those obtained by Hybrid GA. Also, López-Ibáñez et al. (2008) developed an application of the ACO framework for the optimal scheduling of pumps, and presented an explicit representation of optimal pump schedule problem based on time-controlled triggers, where the maximum number of pump switches was specified beforehand. In this representation, a pump schedule was divided into a series of integers with each integer representing the number of hours for which a pump was active/inactive to reduce the number of potential schedules (search space) compared to the binary representation. The proposed representation was adapted to an ACO framework and solved for the optimal pump schedules. Minimization of electrical cost was considered as the objective, while satisfying system constraints. Instead of using a penalty function approach for constraint violations, constraint violations were ordered according to their importance and solutions were ranked based on this order. Ostfeld and Tubaltzev (2008) developed an ant colony methodology for conjunctive least-cost operation of multiple loading pumping in WDSs. The developed optimization problem linked the ant colony scheme with Epanet for the minimisation of the systems and operation costs, taking into account the operational constraints. The decision variables for the operation were the pumping stations pressure heads and the water levels at the tanks for each of the loadings. The constraints were domain pressures at the consumer nodes, maximum allowable amounts of water withdrawals from the sources, and tanks storage closure. The proposed methodology had several model and algorithmic restrictions; it was assumed that the pump efficiencies were constant. Ant colony is a meta-heuristic technique, where there is no general mathematical proof of achieving optimality. ACO is a highly intensive computational method, which might limit the sizes of the systems that could be handled.

2.2.7 Other methods

Other optimization methods to solve the optimal pump schedule were used. Brdys et al. (1988) considered and developed an algorithm for the optimized control schedules for multi-source multi-reservoir water supply schemes of only fixed speed pumps so that the pump control was purely discrete. The developed algorithm was capable of producing sub-optimal or optimal solutions to the associated scheduling problem. The algorithm was based on Lagrangean relaxation of the hydraulic constraints, which couple the pump stations to the network. The method was applied to a practical system, containing two sources and two storage reservoirs, and showed a potential saving, although the method yielded only sub-optimal solution, in the presence of three continuous controlled flows in the network. McCormick and Powell (2004) derived a simplified model from a standard hydraulic simulator. An initial schedule was produced by a descent method, then two-stage Simulated Annealing was used to produce the solutions. Iterative recalibration was employed to ensure that the solution agreed closely with the results from a full hydraulic simulation. The results showed that two-stage Simulated Annealing could produce near-optimal discrete schedules. Further development was still required to include the charges of peak power consumption. Poor results in this case showed that Simulated Annealing could not be assumed that good results would always be obtained without rethinking the model or the neighbourhood structure. Ulanicki and Orr (1991) proposed a unified approach, based on a time distribution function concept for the optimization of general nonlinear hydraulic systems in this approach the optimization problem was decomposed into a two-level structure. The lower-level problems were linear with parameter values taken from the hydraulic model simulator; the upper-level problem was non-smooth, but with linear constraints. The problem properties were studied, such as convexity of the upper-level objective function and non-emptiness of the lower-level constraint sets. In the theory presented, no specific assumptions about the system model were made, and it could be applied to other nonlinear systems. The results showed that the algorithm implementation made a saving of 10% on the total operational cost. Tischer et al. (2003) presented another approach based on spread sheet for optimal pump scheduling. The developed approach used the information about the simplified model from spreadsheet and an optimization solver. The simplified model was mainly based on mass balance equations. The objective function was the overall weekly cost of the system. The decision variables were the outflows of the treatment works and the flows of controlled inter reservoir connections. The constraints were imposed on the reservoir levels and major flows. The overall weekly cost consisted mainly of electrical and chemical costs. The electrical cost was calculated directly from the flows and the electrical tariffs. The pump stations were represented by non-linear power/flow characteristic (regression curves) and were assumed to be unaffected by the changing situation in the remaining network. The advantages of the tool were energy savings, reduction in time spend on preparing the schedules and less skilled staff could prepare the optimised schedules in a repeatable manner, while the major drawback was a lack of a network GUI to build and maintain the optimisation model interactively.

2.3 Methodologies

Different methodologies have been used to achieve the aims and objectives of the current research. Variety of the methodologies has been proposed to cover different areas and aspects of the research and provide different alternatives that can be used in such research areas. The used methodologies are described in the following sections.

2.3.1 Methodology of pressure control using nonlinear programming

In this work, an algorithm for the optimum scheduling of the outlet pressures of the boundary PRVs as well as the internal PRVs has been developed to minimise and smooth the operational service pressure a cross the DMA. The optimal pressure schedule is a continuous nonlinear problem. Third party software, CONOPT 3 has been used as a solver under programming environment called GAMS (Rosenthal 2007). The developed algorithm is based on the hydraulic model of the DMA taking into account the pressure dependent leakage, and is limited to the steady state condition. This means, changes of PRV settings cause instantaneous changes of flows and heads in the network. As a classical optimal control problem, the PRV set-point schedules have been calculated over a given period of time for a given demand and known leakage flow. The components of the optimal pressure control problem are the objective function, the hydraulic model of the network taking into account the leakage model, and operational constraints. Minimising the cost of the total imported flow has been used as an objective function of this optimization problem subject to the operational constraints. The optimization problem of the optimal time schedule of pressure control has been written in GAMS code. A C++ code has been built to create the GAMS code, based on the hydraulic model of the DMA, which has been used to describe the topology and the physical components of the network, such as nodes, pipes and valves, node elevations, etc., and the required demand. An extended content model has been developed to simulate the network with boundary and internal PRVs under the current operation conditions, to provide an initial starting solution for CONOPT to reduce convergence time and to compare the results of optimal pressure control with the current operating conditions.

2.3.2 Methodology of pressure control using a genetic algorithm method

The optimal time schedule of the PRV outlet pressure has been calculated for a given predicted demand and leakage over a specific time horizon. If the predicted demand including the leakage flow is not forecasted correctly, the control performance of applying the optimal time schedule of the PRV outlet pressure will be poor. Instead of finding the optimal time schedule of pressure control, calculating the optimal flow modulation characteristics provides a robust scheme of control strategy. The relationship between the flow and the optimal pressure has been assumed as a polynomial of second order (AbdelMeguid et al. 2009b; Ulanicki et al. 2008a; Ulanicki et al. 2000). Genetic algorithm (GA) has been used to calculate the best coefficients of that polynomial, or to find the optimal flow modulation curve using the hydraulic model of the DMA taking into account the term of pressure dependent leakage. GA toolbox provided in Matlab software has been used to handle this problem and has been linked to Epanet as a hydraulic simulator. Minimising the total leakage flow of the system has been taken as fitness function of this optimization problem and a penalty value has been added if the pressure of the critical nodes violates the allowed minimum service pressure.

2.3.3 Methodology of embedded local hydraulic controller of PRV

In order to apply the optimal pressure control strategies, the AQUAI-MOD® hydraulic controller has been used to modulate the outlet pressure of the PRVs to the optimal setting depending on the flow. In this research, the static and dynamic behaviours of a PRV controlled by AQUAI-MOD® hydraulic controller were experimentally tested. Also, a mathematical model to describe static and dynamic behaviour of the PRV and its AQUAI-MOD® hydraulic controller has been developed. The developed mathematical model has been validated using the data of experimental measurements, and was implemented to the hydraulic model of the water distribution network to represent the dynamic effects of the PRV controlled by AQUAI-MOD® hydraulic controller on the performance of the network (Li et al. 2009), and to enhance the simulations and optimisation models of the WDSs.

2.3.4 Methodology of combined energy and pressure managements

In the current research, integration algorithm between pump scheduling for energy management and DMA pressure control for leakage reduction has been developed. The method involves utilisation of a hydraulic model of the network with pressure dependent leakage and inclusion of a PRV set-points in the set of decision variables. The cost function represents the total cost of water treatment and pumping. An excessive pumping contributes to a high total cost in two ways. Firstly, it leads to high energy usage. Secondly, it induces high pressure, hence increased leakage which leads to more water loss and more energy waste. Therefore, the optimizer, by minimising the total cost, attempts to optimize the energy usage, reduce its cost and minimise the leakage. In the optimisation problem considered some of the decision variables are continuous (e.g. water production, pump speed, and valve setting) and some are integer (e.g. number of pumps switched ON). Problems containing both continuous and integer variables are called mixed-integer problems and are hard to solve numerically. Continuous relaxation of integer variables (e.g. allowing 2.51 pumps ON) enables network scheduling to be treated initially as a continuous optimisation problem solved by a non-linear programming algorithm. Subsequently, the continuous solution can be transformed into an integer solution by manual or automatic post-processing, or by further optimisation (Bounds et al. 2006). The developed energy and pressure management scheduler has been integrated into a modelling environment, called Finesse (Rance et al. 2001). The scheduler, as with all tools in Finesse, is general purpose in that it takes any data model of a network, simulates the network to initialise its decision variables for the network scheduler, and if the model is feasible it calculates the optimal schedules. Using model of a network, Finesse automatically generates optimal network scheduling problem written in a mathematical modelling language called GAMS (Rosenthal 2007), which calls up a non-linear programming solver called CONOPT (Drud 2008) to calculate a continuous optimisation solution. The optimal solution is fed back from CONOPT into Finesse for analysis and/or further processing. The optimal continuous schedule has been then discretized using an automatic algorithm coded in Matlab.

2.3.5 Methodology of optimal feedback rules for operation of pump stations

Typically the real time control for time varying tariffs is implemented in a predictive control fashion, in which an optimal time schedule is calculated ahead over 24 hours period by a solver and recalculated at regular intervals e.g. 1 hour. In order to operate the scheme in real time the solver must be sufficiently fast and this may not always be possible for large water supply systems. In the current study, a methodology for synthesizing feedback control rules has been investigated taking into account a time varying tariff. The rules have been calculated off-line and then can be implemented in local PLCs or in a control room. Once the rules are implemented, the response to the changing state of the water system is instantaneous.

In this research, the feedback rules have been calculated by a GA using Matlab GA toolbox. Each pump station has a rule described by two water levels in a downstream reservoir and a speed for each tariff period. The lower and upper water levels of the downstream reservoir correspond to the pump being ON or OFF.

Chapter 3

3 Management and Control Schemes of Water Supply and Distribution Systems

In this chapter, a brief review about operational control and decision structures for distribution systems are conducted. In addition, descriptions of behavioural equations for modelling water network components that are used in the current study are presented.

3.1 Features of Water Distribution Systems

The following features of WDSs are important from an operational control point of view:

1. Complicated network structure with thousands of connections and many network loops.
2. A typical zone contains one service reservoir to sustain supplies and maintain pressures.
3. Reservoir level variations may have significant impact on flows and pressures of the system.
4. Elements such as booster pumps and control valves control local conditions.

The distribution system has relatively sparse measurements and control. Typically, only a few key flows and pressures are monitored frequently. Local reservoirs are monitored in a similar fashion to those in the supply network. Control elements such as booster pumps and valves have local control loops and may not be monitored continuously. There are few dedicated communications links. Although measurements may be logged locally at frequent intervals, the time-series may only be downloaded to the control room a few times a day or when alarms occur. Often public communications networks are used. Operators in the field download some loggers. There are often temporary meters and loggers installed to investigate specific features of operation.

3.2 Operational Control of Water Supply and Distribution Systems

Operational control of a water system requires co-ordination of the three interacting parts, i.e. the treatment, supply and distribution systems. Typically, each of these sub-systems is considered as a self-contained system for control purposes with boundary conditions to deal with the interactions.

Water systems are spatially distributed and special communication links are required in order to connect remote system areas with the control room. In the past, control consoles contained a substantial number of analogue instruments and indicators difficult to manage by a single person. Now, computer and graphical monitors replaced the analogue instruments, improving significantly compactness of the operator consoles.

For small and medium water networks there is typically one master computer connected to a number of intelligent remote outstations. More control centres are necessary as the scale of the water system increases.

3.3 Control and Decision Structures for Water Distribution Systems

Complex water systems composed of many sub-systems require an adequate control structure. The water network is divided into treatment, supply and distribution parts. The distribution part can include many sub-systems with well-defined boundary flows where each area has dense network of pipes supplying water to customers. The lower layer of the decision structure directly interacts with the physical system by a distributed telemetry system: applies control decisions to the system and collects measurements. An operator in a local control room aided by appropriate hardware and software assesses the sub-system behaviour and sends essential information to the co-ordination level. The responsibilities of the operator can vary from following orders from the upper level to solving some parameterised sub-problems. Schedules for major control elements calculated by the co-ordination level are based on abstract mathematical models and the local operator has to convert them into direct control action taking into account detailed physical layouts of the control elements. The local operator also decides the policy for smaller local pumps and valves. Typically, a computer model of the water network is the basic tool for the operator so the control decisions before being applied to the physical system are verified by this model.

The co-ordination level has a global view of the systems. It works according to the two time horizons. Calculation of the storage policy for one week ahead sets up reservoir level targets for each day. After that, the storage policy and schedules for major elements are evaluated for the next day. The co-ordination level uses sophisticated software tools such as demand forecaster, state estimator and optimal scheduler.

Figure 3.1 illustrates a typical decision and control structure for a complex water system (Brdys and Ulanicki 1994).

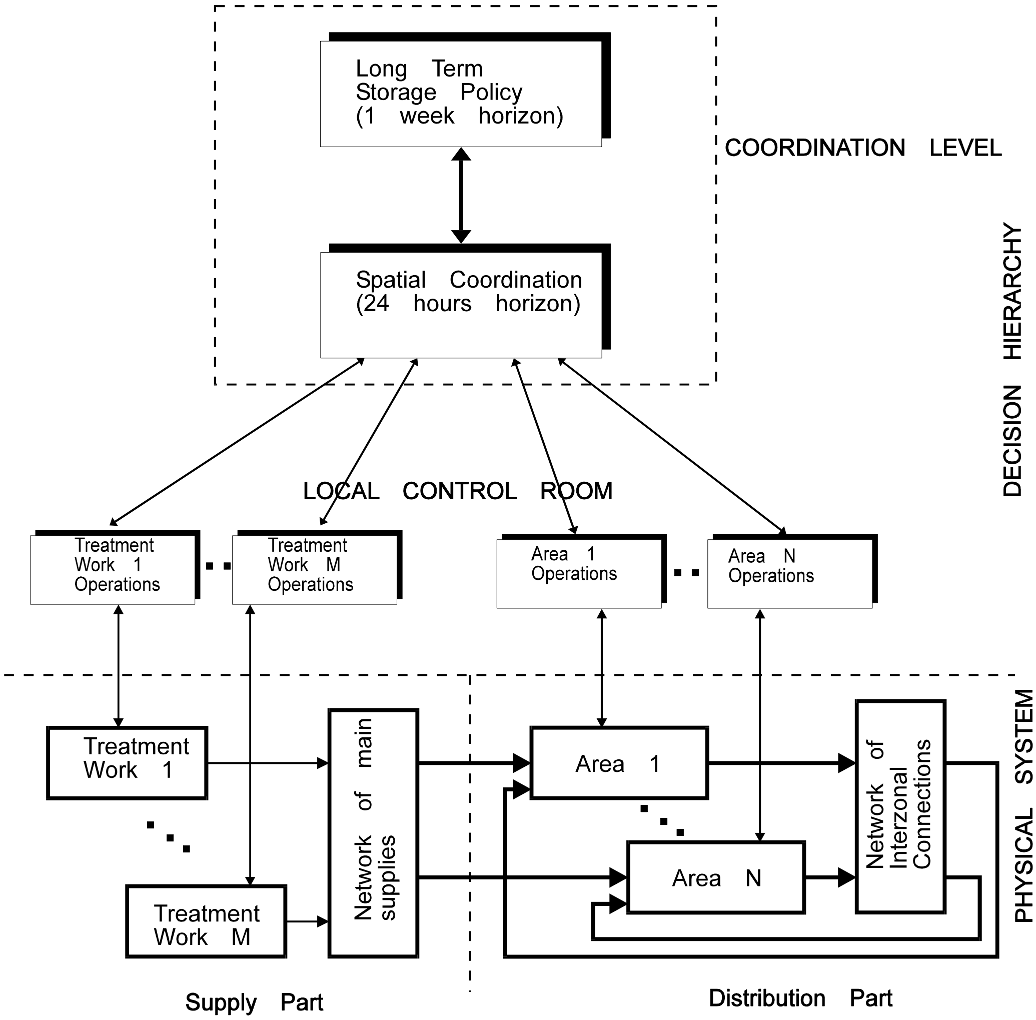


Figure 3.1. Schematics of control and decision structures for water supply and distribution Systems (Brdys and Ulanicki 1994)

3.4 Modelling of Water Networks

Analysis of water distribution network provides the basis for the design of new systems, the extension, and control of existing systems. The flow and pressure distributions across a network are affected by the arrangement and sizes of the pipes and the distribution of the demand flows. Since a change of diameter in one pipe length will affect the flow and pressure distribution everywhere, network simulation is not an explicit process. Optimal design and control algorithms almost invariably incorporate the hydraulic analysis of the system. Pipe network analysis involves the determination of the pipe flows and pressure heads that satisfy the continuity and energy conservation equations.

3.4.1 Mass balance at nodes

Continuity: The algebraic sum of the flows in the pipes meeting at any connection node, together with any external flows, e.g. source flows, demand and leakage flow, is zero.

$$\sum_{l \in N_i^+} q_l - \sum_{l \in N_i^-} q_l = s_i + d_i + l_i \ , \quad i = 1 \rightarrow N_{node} \tag{3.1}$$

Where N_{node} is the total number of nodes, N_i^+ and N_i^- are the set of pipes supplying and carrying out flow from node i. s_i, d_i and l_i are source, demand and leakage flows allocated to node i, respectively. This equation is applicable for each node in the system.

3.4.2 Pressure drop in pipeline due to friction

The pressure drop due to friction in a given length of pipe, expressed in meter of liquid head (Δh), can be calculated using a general formula

$$\Delta h = h_i - h_j = R \cdot q \cdot |q|^{n-1} \tag{3.2}$$

where h_i and h_j are the head at the origin node i and destination node j. R is the pipe resistance and n is the head loss equation exponent. Both R and n depend on method used in the system analysis.

Many pipe flow formulas available that describe the relation of flow and head loss under various flow patterns. The most typical formulas are the Darcy-Weisbach, Colebrook-White, and Hazen-Williams equations (Brown 2002; Haktanır and Ardıçlıoğlu 2004; Liou 1998; Travis and Mays 2007). The Darcy-Weisbash equation combined with Colebrook-White formula is an accurate representation over wide range of flow regimes but requires more computational effort than Hazen-Williams equation (Liou 1998; Travis and Mays 2007).

3.4.2.1 Darcy Weisbach formula

A more accurate (physical) formula to calculate the head loss in pipes is the Darcy-Weisbach formula,

$$\Delta h = f \frac{L}{D} \frac{v^2}{2g} \tag{3.3}$$

where f is Darcy friction factor, dimensionless, usually a number between 0.008 and 0.10, L and D are the pipe length and the diameter in [m], v is the average flow velocity in the pipe, and g is acceleration due to gravity, 9.81 m/s^2.

Regarding to the general equation of the head loss equation(3.2), n equal 2 and R is defined as follows:

$$R = f \frac{8}{g\pi^2} \frac{L}{D^5} \tag{3.4}$$

Friction Factor

For laminar flow, with Reynolds number Re<2000, the Darcy friction factor f is calculated from the simple relationship

$$f = \frac{64}{\mathrm{Re}} \tag{3.5}$$

It can be seen from equation (3.5) that for laminar flow the friction factor depends only on the Reynolds number and is independent of the internal condition of the pipe. Thus, regardless of whether the pipe is smooth or rough, the friction factor for laminar flow is a number that varies inversely with the Reynolds number.

Colebrook-White formula

For turbulent flow, when the Reynolds number Re>4000, the friction factor f depends not only on Re but also on internal relative roughness (e/D) of the pipe. As the pipe relative roughness increases, so does the friction factor. Therefore, smooth pipes have a smaller friction factor compared with rough pipes. Various formulas exist for calculating the friction factor f. These are based on experiments conducted by scientists and engineers over the last 60 years or more. A good all-purpose equation for the friction factor f in the turbulent region (i.e., where R>4000) is the Colebrook White equation:

$$\frac{1}{\sqrt{f}} = -2\log_{10}\left[\frac{(e/D)}{3.7} + \frac{2.51}{\mathrm{Re}\sqrt{f}}\right] \tag{3.6}$$

where e is absolute pipe roughness in [m].

It can be seen from equation (3.6) that the calculation of f is not easy, since it appears on both sides of the equation. A numerical iterative approach needs to be used.

3.4.2.2 Hazen-Williams equation

Hazen-Williams equation is commonly used in the design and modelling of water distribution network and in the calculation of frictional pressure drop. This method involves the use of Hazen-Williams coefficient instead of pipe roughness or liquid kinematic viscosity. The pressure drop calculation using Hazen Williams equation takes into account flows, pipe diameter, and specific gravity as follows:

$$\Delta h = \frac{\kappa \cdot L \cdot q^{1.852}}{C \cdot D^{4.87}} \tag{3.7}$$

where C is Hazen-Williams coefficient, dimensionless, q is flows in (l/s), and κ is constant factor which depends on the unit used for L, D and q.

Referring to general equation(3.2), n equals to 1.852 and R is defined as:

$$R = \frac{\kappa \cdot L}{C \cdot D^{4.87}}$$

Historically, many empirical formulas have been used to calculate frictional pressure drop in pipelines. Hazen-Williams equation has been widely used in the analysis of pipeline networks and WDSs because of its simple form and ease of use in analysing an entire network.

3.4.3 Minor losses

In most long-distance pipelines, such as trunk lines, the pressure drop due to friction in the straight lengths of pipe forms the significant proportion of the total frictional pressure drop. Fully opened valves and fittings contribute very little to the total pressure drop in the entire pipeline. Therefore, pressure losses through valves, fittings, and other restrictions are generally classified as “minor losses”. In long pipelines the minor losses may be neglected without significant error.

3.4.4 Losses in valves

Experiments with fluid flow at high Reynolds numbers have shown that the minor losses vary approximately with the square of the velocity. This leads to the conclusion that minor losses can be represented by a function of the liquid velocity head or kinetic energy ($u^2/2g$). Accordingly, the pressure drop (head loss through valves) is generally expressed in terms of the liquid kinetic energy ($u^2/2g$) multiplied by a head loss coefficient K. Therefore, the pressure drop in a valve is calculated as follows

$$\Delta h = K \frac{u^2}{2g} \tag{3.8}$$

The value of K is determined by the flow or by the shape of the valve and the aperture percent.

3.4.5 Pumps stations

Pumping stations are facilities including pumps and equipment for pumping water from water treatment work (WTW) to service reservoirs or boost the delivered pressure at remote areas. Pumps are the only positive elements in water networks, which import energy to the system. A pump curve or characteristic shows a relationship between its two main parameters flow and pressure. Pumps should be selected to fit the required hydraulic duties in terms of delivering required demand at certain pressure at the maximum efficiency to minimise the pumping energy under a wide operation conditions (Ulanicki et al. 1993). For a system of u parallel identical pumps of speed s, the relation between the group flow, q and the delivered pressure increase, Δh is expressed as

$$\Delta h = s^2 \left(A\left(\frac{q}{u \cdot s}\right)^2 + B\left(\frac{q}{u \cdot s}\right) + C \right) \tag{3.9}$$

where A, B and C are pump characteristic coefficients, and measured experimentally or provided by the manufacture. The required power, W, to run this system is calculated as

$$W = \frac{\rho g \Delta h q}{\eta} \tag{3.10}$$

Where ρ, g, η are water density, gravitational acceleration, and the pump efficiency, respectively. Also the pump efficiency depends on the pump flow and speed and can be represented in a parabolic form as in the following equation (Ulanicki et al. 2008b).

$$\eta(q,u,s) = a\cdot\left(\frac{q}{us}\right)^3 + b\cdot\left(\frac{q}{us}\right)^2 + c\left(\frac{q}{us}\right) \tag{3.11}$$

Where a, b and c are pump efficiency coefficients and depend on the pump maximum efficiency flow and the pump cut-off flow. To estimate the required power to run the pump station, equation (3.10) is reformulated as

$$W = \frac{\rho g q}{\eta} \frac{s^2\left(A\left(\frac{q}{u\cdot s}\right)^2 + B\left(\frac{q}{u\cdot s}\right) + C\right)}{a\cdot\left(\frac{q}{us}\right)^3 + b\cdot\left(\frac{q}{us}\right)^2 + c\left(\frac{q}{us}\right)} \tag{3.12}$$

Using equation (3.12) to compute the required power to run the pump station in non-linear optimization solvers, may lead to singularity, which some time and for complex systems leads to non-feasible solution or non-convergent optimization problem. For this reason, another representation of power characteristics which was proposed by Ulanicki et al. (2008b) has been used in the current study. Ulanicki et al. (2008b) proposed two approaches for efficiency and mechanical input power of a group of parallel identical pumps. In the first approach, the power characteristic was evaluated from hydraulic and efficiency curves, while in the second approach, the mechanical power was approximated directly by a cubic polynomial and scaled by the pump speed and the number of pumps. The second approach could lead to a more accurate representation for use in simulation and optimization models, if the power data points are available. The proposed cubic formula of the power is depicted below

$$W = us^3 \left(E\left(\frac{q}{us}\right)^3 + F\left(\frac{q}{us}\right)^2 + G\frac{q}{us} + H \right) \tag{3.13}$$

where E, F, G , and H are pump power coefficients, and measured experimentally or provided by the manufacture.

3.4.6 Conservation of energy

The energy must be conserved between any two points and does not depend on the path between node i and j. Along a path between nodes i and j energy can be written as:

$$h_i - h_j = \sum_{l \in l_{path}} \Delta h_l - hp_l = \sum_{l \in l_{path}} R_l \cdot q_l \cdot |q_l|^{n-1} - hp_l \tag{3.14}$$

where h_i and h_j are the total head at nodes i and j, Δh_i , R_l, q_l are the head loss, loss equation coefficient and flows in pipe l, n is the exponent from the head loss equation, and hp_l is the head generated by the pump in line l. l_{path} defines the set of links in the path. Equation (3.14) can be written for a closed or pseudo loop or a single pipe.

Any water distribution network can be broken up into a minimum number of independent loops. As it turns out, these loops can be found directly by calculating the minimum spanning tree (Arsene et al. 2004a, b). A closed loop is one that begins and ends at the same node. Thus, from energy conservation concept, the algebraic sum of the head losses in the pipes, valves, together with any heads generated by pumps, around any closed loop formed by links is zero.

$$h_i - h_j = \sum_{l \in l_{loop}} \Delta h_l - hp_l = 0 \tag{3.15}$$

where, l_{loop} defines the set of links in the closed loop.

A pseudo-loop is a path of links between two nodes of known total head, like a reservoir or a tank. Pseudo-loop equations include additional information regarding the flow distribution, and are needed for some solution methods.

3.4.7 Background leakage and burst model

Leakage is usually classified into background and burst leakage. Background leakage occurs through numerous connections, joints and fittings, and depends on the operational services pressure in pipes. Pressure control for leakage reduction is appropriate to the background leakage. Several mathematical models to relate the leakage and operating pressure are proposed and based on experimental results (Brown 2007; Giustolisi et al. 2008; Koppel et al. 2007; Shammas and AI-Dhowalla 1993).

For non-metered WDSs, the minimum night flow (MNF) is used as an indicator of the total leakage. The estimated total value of network background leakage needs to be distributed over the nodes in the network model. Most of background leakage is through connections and fittings and therefore, the leakage flow has been assumed to be distributed between the nodes proportionally to the number of properties connected to each node or to the node demand.

The leakage-pressure relationship is represented by equation(3.16), which has been added to the standard hydraulic equations of a water network to create an extended model suitable for pressure control and leakage analysis.

$$l(t) = k \cdot P(t)^{\alpha} = k \cdot (h(t) - H)^{\alpha} \tag{3.16}$$

where $l(t)$, $P(t)$ and $h(t)$ are nodal leakage flow, nodal pressure and total head at time t, k and α denote the leakage coefficients and exponent respectively, and H denotes the elevation of the node. The leakage has been assumed to be distributed between all nodes proportional with demand. The leakage exponent α changes from 0.5 to 2.5 depending on the type of leakage, material of pipes and the soil (Giustolisi et al. 2008; Noack and Ulanicki 2006; Shammas and AI-Dhowalla 1993; Thornton and Lambert 2005; Ulanicki and Prescott 2006; Wu et al. 2010). In the current study the leakage exponent α has been chosen to be a constant and equal 1.1 as recommended by many pervious works (Alonso et al. 2000; Germanopoulos 1995; Jowitt and Xu 1990), while the coefficient k depends on the demand at each node and has been computed as depicted by equations (3.17) to (3.22). In equation (3.17), it has been assumed that the summation of the total leakage is equal to MNF, $q(t_{\min})$, which occurs at the time t_{min}.

$$q(t_{\min}) = \sum_{i} l_i = \sum_{i \in N_d} k_i \cdot P_i(t_{\min})^{1.1} \tag{3.17}$$

where $d_i(t_{\min})$ and $P_i(t_{\min})$ denote the demand and pressure of node i at time $t_{\min}$, respectively. As the leakage at any node has been assumed to proportional with the node demand, then the coefficient k_i is proportional with the demand of node i at the time of the MNF, $t_{\min}$ as in equation (3.18)

$$k_i \propto d_i\left(t_{\min}\right) \tag{3.18}$$

By introducing proportional coefficient β_i, the coefficient k_i can be expressed as below

$$k_i = \beta_i \cdot d_i\left(t_{\min}\right) \tag{3.19}$$

The pressure at node i is a difference between node head, h_i, and node elevation, H_i, as given in equation (3.20).

$$P_i\left(t_{\min}\right) = \left(h_i\left(t_{\min}\right) - H_i\right) \tag{3.20}$$

Substitute equations (3.19) and (3.20) for k_i and $P_i(t_{min})$ in equation (3.17)

$$q\left(t_{\min}\right) = \sum_i l_i = \sum_{i \in N_d} \beta_i \cdot d_i\left(t_{\min}\right) \cdot \left(h_i\left(t_{\min}\right) - H_i\right)^{1.1} \tag{3.21}$$

Hence the MNF, the demand and total head of node i at t_{min} are known from the data provided in the hydraulic model and simulation results, the proportional coefficient β_i, which has been used to calculate the leakage coefficient k_i, is estimated as below

$$\beta_i = \frac{q\left(t_{\min}\right)}{\sum_i d_i \cdot \left(h_i\left(t_{\min}\right) - H_i\right)^{1.1}} \tag{3.22}$$

3.4.8 System of equations for hydraulic network

The unknowns in a steady state hydraulic analysis of water distribution networks are the flow in each link (pipes, valves and pumps), q, and total head at each node, h. In a network with N_{node} nodes and N_{link} links, the total number of unknowns is $N_{node}+N_{link}$. Four types of equation formulations can be developed to solve for these unknowns. They can be expressed in terms of unknown link flows or nodal heads. The system of equation is non-linear due to the head loss relationships and require iterative solutions. Newton Raphson method is the most widely used iterative solution procedure in water network analysis. The four solution approaches are discussed briefly below, and more detailed information can be found in (Boulos et al. 2006; Brdys and Ulanicki 1994).

3.4.8.1 Loop model formulation

The smallest number of equations is the loop model equations that include one equation for each closed loop and pseudo-loop *i.e* N_{loop}+N_{ploop} equations, where N_{loop} and N_{ploop} are the number of closed loop and pseudo-loop, respectively. The unknowns in the loop equations are Δq's variable which is defined as corrections to flows around each loop. Beginning with flow distribution, which satisfies the conservation of mass equation(3.1) , the corrections maintain those relationships. When zero flow corrections are found in all loops, the iteration stops and loop flows are found. After the flows are determined, equation(3.14) is applied starting at a node of known total head to determine the unknown nodal heads.

Hardy Cross method is one approach to solve the loop equations, which was developed by the US engineer Hardy Cross and also known as the relaxation method. This approach is used to analyse water supply networks, and works on the principle of balancing circuit pressure drop by correcting assumed flows for each loop independently of the other loops then applies the corrections to compute the new link flows (Cross 1936). In Hardy cross method, each loop correction is determined independently, but several loops may have common links so corrections to those loops influence the head losses around more than one loop. The method is easily implemented by hand calculation or in a spreadsheet (Lopes 2004).

Newton-Raphson method is another more efficient method, which simultaneously solves for all loop corrections, which is originally applied for pipe network analysis by (Shamir and Howard 1968). Newton-Raphson method is later improved and applied for different network application (Brkić 2009; Ypma 1995).

Linear theory method for solving the loop equation system simultaneously is more efficient approach by simultaneously computing flows for all loops (Wood and Charles 1972).

3.4.8.2 Node-Loop model formulation

A modified linear theory method by coupling the loop equation with the node equations was developed by Wood and Rayes (1981). The modified linear theory solves directly for the link flows, q. The N_{loop}+N_{ploop} loop equations incorporate the concept of energy conservation equation(3.14) and N_{node} equations incorporate conservation of mass equation(3.1). The total number of independent equations is N_{loop}+N_{ploop}+N_{node} that number equal to the number of unknowns link flow, N_{link}. This system of equations cab also be solved iteratively by applying the Newton-Raphson method, which solves the system of equations for the link flows directly. Once the link flows are found, they are substituted to node equations starting at a node of known total head to determine the nodal heads.

3.4.8.3 Node model formulation

The node equation can be rewritten in terms of nodal heads by writing equation (3.2) for pipe l that connects nodes i and j as

$$q_l = \frac{\left(h_i - h_j\right)\left|h_i - h_j\right|^{1-1/n}}{R_l^{1/n}} \tag{3.23}$$

This term for each link is substituted for the flow in equation(3.1). This substitution combines the conservation of energy and mass relationships resulting in N_{node} equations in terms of the N_{node} unknowns of nodal heads, h. This system of nonlinear equation can be solved using Newton-Raphson method, and after the nodal head are computed, they can be substituted in equation(3.23) to compute the links flows (Boulos et al. 2006).

3.4.8.4 Mixed model formulation

The previous methods solve for the pipe flows, q, or nodal head, h, in a nonlinear solution scheme then use conservation of energy to determine the other set of unknowns. The mixed system of equations includes the conservation of mass equation (3.1) for each node with respect of link flows and the conservation of energy equation (3.14) of each link including both link flows and nodal heads. The number of equation in this system equal to N_{node}+N_{link} and is greater than the systems of other methods, however the solution time to find the true values of nodal heads and links flows is similar or better. In addition, the algorithm does not require defining loops that may be a time consuming task. This method is also known as the hybrid or gradient approach (Brdys and Ulanicki 1994).

Chapter 4

4 Overview of the Optimization Methods Used in This Study

In this chapter, a general definition of the optimization problem is formulated, followed by a brief overview of the optimization methods and solvers that have been used in this study.

Optimization problems arise naturally in many engineering applications. Control problems can be formulated as optimization problems in which the variables are inputs and states, and the constraints include the model equations for the system. At successively higher levels, optimization can be used to determine set-points for optimal operations, to design processes and systems, and to plan for future capacity. Optimization problems contain the following key ingredients:

1. Decision variables that are real numbers, integers, or binary are the most common types.
2. Constraints that define allowable values or scopes for the variables, or that specify relationships between the variables.
3. An objective function that measures the desirability of a given set of variables.

The optimization problem is a problem to choose values of variables that satisfy the constraints and minimizes the objective function.

Different methods can be used to solve the optimization problem including mathematical programming, evolutionary algorithm (EA), etc. The term “mathematical programming”, is synonymous with optimization. Correspondingly, linear optimization (in which the constraints and objective are linear functions of the variables) is usually known as “linear programming”, while optimization problems that involve constraints and have nonlinearity present in the objective or in at least some constraints, are known as “non-linear programming (NLP)” problems. In convex programming, the objective is a convex function and the feasible set (the set of points that satisfy the constraints) is a convex set. In quadratic programming, the objective is a quadratic function while the constraints are linear. Integer programming problems are those in which some or all of the variables are required to take integer values.

While, an EA is a subset of evolutionary computation, a generic population based metaheuristic optimization algorithm. An EA uses some mechanisms inspired by biological evolution: reproduction, mutation, recombination, and selection. Candidate solutions to the optimization problem play the role of individuals in a population, and the fitness function determines the environment within which the solutions exist. EAs often perform well approximating solutions to all types of problems because they ideally do not make any assumption about the underlying fitness function. Genetic Algorithm (GA) is the most popular type of EA, which seeks the solution of a problem in the form of strings of numbers, by applying operators such as recombination and mutation.

NLP and GAs have been used in the current study in both the optimal pressure control problem and optimal pump schedule, in order to reduce the leakage and energy consumption in WDSs, respectively.

4.1 Nonlinear Programming

NLP problems are constrained optimization problems with nonlinear objective and/or constraint functions. If any of the variables are required to take integer values, the problem is a mixed-integer NLP problem. A constrained NLP problem can be expressed as follows

$$\begin{aligned}
&\text{max (or min) } z = f\left(x\right) \\
&\text{subject to} \quad \begin{cases} g_i(x) \le b_i, & i = 1, \ldots m \\ h_j(x) = 0, & j = 1, \ldots n \end{cases} \\
&\text{where} \quad x \in R^n
\end{aligned} \tag{4.1}$$

where $f(x)$, $g_i(x)$ and $h_j(x)$ are given objective, inequality and equality constraints functions, respectively of the decision variables $x = (x_1, x_2, \ldots, x_n)$.

There are many techniques available for the solution of a constrained NLP problem. All the methods can be classified into two broad categories: direct methods and indirect methods. In the direct methods, the constraints are handled in an explicit manner, whereas in most of the indirect methods, the constrained problem is solved as a sequence of unconstrained minimization problems. The major approaches represented in production software packages are sequential quadratic programming (Nocedal and Wright 1999), reduced gradient (Bazaraa et al. 2006; Rao 1996) (direct methods), sequential linearly constrained (Nocedal and Wright 1999), and augmented Lagrangian multipliers methods (Nocedal and Wright 1999) (indirect methods).

The use of nonlinear models is essential in some applications, since a linear or quadratic model may be too simplistic and therefore produce useless results. However, there are some disadvantages for using the more general nonlinear paradigm. For one thing, most algorithms cannot guarantee convergence to the global minimum, i.e., the value x^* that minimizes f over the entire feasible region. At best, they will find a point that yields the smallest value of f overall points in some feasible neighbourhood of solution. (An exception occurs in convex programming, in which the functions f, g_i, and h_j are convex. In this case, any local minimum is also a global minimum) (Bazaraa et al. 2006). The problem of finding the global minimum is an extremely important in many applications.

A second disadvantage of NLP is that general-purpose software is somewhat less effective because the nonlinear paradigm encompasses such a wide range of problems with a great number of potential pathologies and eccentricities. Even when the solution is close to a minimiser x^*, algorithms may encounter difficulties because the solution may degenerate specially if the Jacobean of the problem is singular (Nocedal and Wright 1999).

Finally, some of the software treats the derivative matrices as dense, which means that the maximum dimension of the problems they can handle is limited. However, others use sparse algebra, and are therefore equipped to handle large-scale problems (Wright 1999).

Algorithms for special cases of the NLP, such as problems with linear constraints or constraints in the form of bounds on components of x, tend to be more effective than algorithms for the general problem because they exploit the special properties of the optimization problem.

Optimization technology is traditionally made available to users by means of packages for specific classes of problems (Wright 1999). Data is communicated to the software via simple data structures and subroutine argument lists, user-written subroutines (for evaluating nonlinear objective or constraint functions), text files in the standard format, or text files that describe the problem in certain vendor-specific formats.

More recently, modelling languages have become an appealing way to interface to packages, as they allow the user to define the model and data in a way that makes intuitive sense in terms of the application problem. Optimization tools also form part of integrated modelling systems such as GAMS (Rosenthal 2007) (which has been used in the current study) and or use spreadsheets interface such as Microsoft's Excel interface.

4.1.1 CONOPT

The reduced gradient approach has been implemented and used by CONOPT (Drud 1994, 2008). This approach uses the formulation in which only bounds and equality constraints are present. Reduced gradient algorithms partition the components of x into three classes: basic, fixed, and superbasic variables. The equality constraint $h(x)=0$ is used to eliminate the basic components from the problem by expressing them implicitly in terms of the fixed and superbasic components. The fixed components are those that are fixed at one of their bounds for the current iteration. The superbasics are the components that are allowed to move in a direction that reduces the value of the objective z. Strategies for choosing this direction are derived from unconstrained optimization; they include steepest descent (Rao 1996), nonlinear conjugate gradient (Nocedal and Wright 1999), and quasi-Newton strategies (Nocedal and Wright 1999 ; Rao 1996). CONOPT use sparse linear algebra techniques during the elimination of the basic components, making them suitable for large-scale problems.

CONOPT is available as a NLP solver for most modelling systems, e.g. AIMMS (Roelofs and Bisschop 2010), AMPL (Fourer et al. 2002), GAMS (Rosenthal 2007), LINDO/LINGO (LINDO 2010), MPL (MAXIMAL 2011), and TOMLAB (Holmström et al. 2010). CONOPT is also available as a subroutine library or DLL, but the modelling system versions are recommended for all but the most sophisticated power-users.

CONOPT is continuously being updated, mainly to improve reliability and efficiency on large models and on special classes of models. There is a sub-components for very large square sets of nonlinear equations (over 1 million variables and equations), a sequential linear programming component for almost linear models (also useful while finding a feasible solution), a sequential quadratic programming component for models with many degrees of freedom, and a steepest edge component for very difficult models. The choice between the components is in most case done dynamically based on performance statistics. More details about GAMS code and CONOPT are presented in Appendix A.

4.1.2 Disadvantages of NLP

NLP is an important branch of operations research and has wide applications in the areas of military, economics, engineering, and science management. There are several types of traditional methods for NLP (Rao 1996), however, since there are many local optimizations for NLP, most of the solution methods may solve it only on an approximate basis. Recently, many researchers have used and proposed some new stochastic optimization methods, such as the GA (Gupta et al. 1999; Hua and Huang 2006; Lavric et al. 2005), Simulated Annealing (Mays 2004; McCormick and Powell 2004; Tospornsampan et al. 2007), Tabu search (Cunha and Ribeiro 2004; Glover et al. 1995), and various hybrid methods (Fung et al. 2002; Tu et al. 2005; van Zyl et al. 2004).

The development and use of NLP models is well established. However, the use of many models has been restricted where the problem is large in size and there are a large number of non-linear interactions. In most cases, the use of linear approximations (Cai et al. 2001; Germanopoulos 1995; Sterling and Bargiela 1984) or simplification of the model (Shamir and Salomons 2008; Ulanicki et al. 1996) has been necessary in order to find a solution.

4.2 Genetic algorithms (GA)

GA are an evolutionary optimisation approach, which was first proposed by (Holland 1975), and is one of the most important stochastic optimization methods. As an intelligent optimization method, GA has made great achievements in the solution to travelling salesman problems, transport problems, 0-1 programming problems, and multi-objective optimization problems. However, it has made little contribution to NLP problems (Aryanezhad and Hemati 2008; Tang et al. 1998). In fact, in the construction and application of GA to NLP problems, coding and decoding processes are important and difficult. In addition, handling system constraints, especially the measurement and evaluation of illegal chromosomes (points) are key techniques with GA. Currently, several methods have been developed to deal with system constraints and were reviewed by (Rao 1996). Among of which, a large penalty in the construction of the fitness function was often used to evaluate the infeasible solutions, but this narrows the search space, by eliminating all infeasible points from the evolutionary process, and may lessen the ability to find better candidates for the global optimization. Mixed Integer Nonlinear problems were solved by means of GA with a special penalty function proposed by (Li and Gen 1996). The penalty function method was used to construct fitness function to evaluate chromosomes generated from genetic reproduction.

GA are an alternative to traditional optimisation methods, and are most appropriate for complex non-linear models where location of the global optimum is a difficult task (Cai et al. 2001; Simpson et al. 1994). Therefore, GA appears to be a potentially useful approach, which has been employed to find the optimal PRV flow modulation characteristics, and optimal feedback rules for pump stations in the current study.

GAs follow the concept of evolution by stochastically developing generations of solution populations using a given fitness or objective function. They are particularly applicable to problems, which are large, nonlinear and possibly discrete in nature, features that traditionally increase complexity of the problem. Due to the probabilistic nature, GAs do not guarantee optimality of the solution. However, they are likely to be close to the global optimum. This probabilistic nature of the solution is also the reason they are not contained by local optima (Mardle and Pascoe 1999).

GAs were widely employed for different applications in WDSs. Such as, optimal design of water network (Kadu et al. 2008; Savic and Walters 1997; van-Vuuren 2002; Walters et al. 1999), water network rehabilitation (Halhal et al. 1997), leak detection (Vítkovský et al. 2000; Wu and Sage 2006), model calibration (Borzì et al. 2005; Schaetzen et al. 2000), optimal time schedule for pump operation (Beckwith and Wong 1995; Boulos et al. 2002; Kelner and Léonard 2003 ; Mackle et al. 1995; Savic et al. 1997; Wang et al. 2009; Wei and Leung 2008) water quality issues (Gibbs et al. 2010; Tu et al. 2005; Wei and Leung 2008). The problem of optimal time schedule for the pressure regulation in water distribution networks was introduced by using GA (Awad et al. 2009; Awad et al. 2003).

The availability of open source GA libraries in different programming languages, and the free hydraulic simulators such as Epanet provides a cost free optimisation tool for different applications. Once the link between GA library and the hydraulic simulators is established, then the system becomes very powerful tool for applying GA optimization techniques to any of water distribution applications, e.g., pressure control, pump scheduling, water quality control, optimal network design, etc.

4.2.1 Genetic Algorithm overview

Computer implementations of GAs are based on a population of abstract representation (called chromosomes or the genotype of the genome) of candidate solutions (called individuals, creatures, or phenotypes) which evolve toward better solutions. The evolution usually starts from initial population of randomly generated individuals and progress through generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Typically, the algorithm terminates when either a maximum number of generations has been reached, or a satisfactory fitness level has been found for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

A typical GA requires:

1. a genetic representation of the solution domain,
2. a fitness function to evaluate the solution domain.

A standard representation of the solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case.

The fitness function is defined over the genetic representation and measures the quality of the represented solution. The fitness function is always problem dependent. In some problems, it is hard or even impossible to define the fitness expression; in these cases, interactive GAs are used.

Once the genetic representation and the fitness function are defined, GA proceeds to initialize a population of solutions randomly, then improve it through repetitive application of mutation, crossover, inversion and selection operators. Figure 4.1 lists a pseudo code of the standard GAs, showing the main operations and procedure included in GA.

```
begin GA
        K:=0  {generation counter}
        Initialize population Pop(K)
        Evaluate population Pop(K)  {i.e., compute fitness values}
        while (not done) do
                K:=K+1
                Select Pop(K) from Pop(K-1)
                Crossover Pop(K)
                Mutate Pop(K)
                Evaluate Pop(K)
        end while
end GA
```

Figure 4.1 Pseudo-code of the standard GA

4.2.1.1 Initialization

Initially many individual solutions are randomly generated to form an initial population. The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, covering the entire range of possible solutions (the search space). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

4.2.1.2 Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a fitness-based process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as this process may be very time-consuming. Most functions are stochastic and designed so that a small proportion of less fit solutions are selected. This helps keep high diversity of the population large, preventing premature convergence on poor solutions. Selection alone cannot introduce any new individuals into the population, i.e., it cannot find new points in the search space. These are generated by genetically-inspired operators, of which the most well known are crossover and mutation.

4.2.1.3 Evolution

The next step is to generate a second generation population of solutions from those selected through genetic operators: crossover, and/or mutation.

The Crossover is performed with crossover probability or crossover rate between two selected parents, by exchanging parts of their genomes (i.e., encodings) to form two new individuals, called offspring. This operator tends to enable the evolutionary process to move toward promising regions of the search space. Although reproduction methods that are based on the use of two parents are more "biology inspired", some research suggests more than two "parents" are better to be used to reproduce a good quality chromosome(Gong and Rum 2004; Tsutsui and Jain 1998).

The mutation operator is introduced to prevent premature convergence to local optima by randomly sampling new points in the search space. It is carried out by flipping bits at random, with mutation probability.

These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions.

4.2.1.4 Termination

GAs are stochastic iterative processes that are not guaranteed to converge; the termination condition may be specified as some fixed maximum number of generations or as the attainment of an acceptable fitness level. This generational process is repeated until a termination condition has been reached. Common terminating conditions are:

- A solution is found that satisfies minimum criteria
- Fixed number of generations reached
- Allocated computation time reached
- The highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results
- Manual inspection
- Combinations of the above

A standard GA flow chart format is depicted in Figure 4.2.

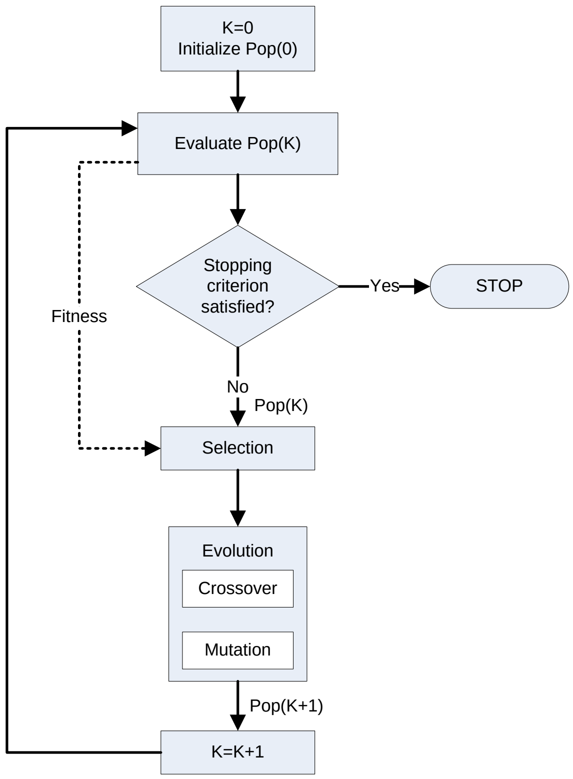


Figure 4.2 Flowchart of the standard GA

Chapter 5

5 Pressure and Leakage Management in Water Distribution Systems

5.1 Introduction

Despite operational improvements over the last 10-15 years, water utilities still lose a significant amount of potable water from their networks through leakage. The most effective way to combat leakage is on one hand to locate and physically repair bursts and on the other hand to introduce pressure control to reduce background leakage from connection and joints. Reduction of leakage has two positive impacts on the environment - it minimises clean water losses and energy used for pumping and treatment of water. There are two solutions recommended by existing literature, time modulation which is an optimal time schedule for a PRV set-point or alternatively flow modulation where the set-point changes relate to flow through the valve. Both time and flow modulation can be applied to a single inlet DMA. Time modulation can be applied to multi-inlet DMA but it is not always possible for flow modulation due to the risk of hunting. In this latter case special arrangements may be required to co-ordinate valve operations e.g. master-slave arrangements (Ulanicki et al. 2000).

In this chapter, a fast and efficient method to calculate the optimal time schedules and flow modulation curves is presented. It is convenient to distinguish between boundary and internal PRVs. They have been treated differently in the formulated optimization problem, the decision variable for a boundary valve is PRV set-point (Ulanicki et al. 2000) whereas for the internal valves is a valve resistance (Vairavamoorthy and Lumbers 1998). Then, the resistance has been automatically translated into a set-point for field implementation. The time modulation methodology is based on solving a NLP problem with equality constraints represented by a hydraulic model with pressure dependent leakage term and inequality constraints representing operational requirements (e.g. pressure at critical nodes). The cost of boundary flows which include leakage flows has been minimized. An extended content model with pressure dependent leakage has been developed and solved to provide starting point for quick convergence. Optimal time schedules have been converted into flow modulation curves by plotting scatter plots of flows against heads. The algorithm has been implemented as a module in the Finesse package (Rance et al. 2001) and allows to solve complete pressure control tasks. A user needs to provide a hydraulic model, leakage information and leakage characteristic – leakage coefficient and the exponent in the pressure power law as discussed in section “3.4.7”. The program calculates time schedules and also flow modulation curves for single and multi-inlet PRVs. Evaluation of optimal control strategies and benefit analysis in terms of leakage reduction for the two case studies provided by Yorkshire Water Services are included.

5.2 Problem Outline

Currently, it is a common practice for water utilities to divide the water distribution networks into district metered areas (DMAs) with closed boundaries except for a small number of metered inlets and outlets. This structure facilitates applying pressure management schemes to those areas. Current control strategies operate output pressure of the PRV, which control inlet pressures to the DMA. The outlet pressures of the PRVs are based on the minimum values, which can satisfy minimum service pressures for customers with safety margin. Low operational pressures result in reduced leakage and minimisation of the risk of bursts. Pressure management is now recognised as one of the most cost effective methods to reduce leakage in water networks and is implemented by most water companies (Araujo et al. 2003; Ulanicki et al. 2000; Vairavamoorthy and Lumbers 1998).

In this work, an algorithm for the optimum scheduling of the outlet pressures of the inlet boundary PRVs as well as the internal PRVs has been developed to minimise and smooth the operational service pressure a cross the DMA. This algorithm is based on calculating the optimal PRVs schedules for given demand incorporated with the pressure dependent leakage model. In the current study, the algorithm of the pressure control is limited to the steady state condition. This means, changes of PRV settings cause instantaneous changes of flows and heads in the network. The PRV set-point schedules have been calculated over a given period of time, the novelty of the approach presented here is inclusion of both boundary and internal PRVs in the problem formulation. The components of the optimal pressure control problem are the objective function, the hydraulic model of the network taking into account the pressure dependent leakage model, and operational constraints.

5.3 Mathematical Formulation

A WDS consists of a group of interconnected nodes and reservoirs by various types of elements such as pipes, valves, and pumps. Each element in the network has been modelled by a mathematical equation that describes the relationship between the element flow and the head loss across the origin and destination nodes of the element. The form of the relationship depends on the physical characteristics and the properties of the element. The system governing equations can be expressed in accordance with the (1) nodal mass conservation rule - the total sum of all the inlet and outlet flows at each node equals to zero; and (2) Energy conservation rule - the total sum of the all head losses around any loop in the network equals to zero, described in chapter 3.

5.4 Extended Hydraulic Model

The content model of hydraulic network was initially developed by (Collins et al. 1978), which solved the network system of equation by optimization method. In this work, an extended content model with pressure dependent leakage has been developed and solved to provide starting point for quick convergence.

5.4.1 Components and nodal heads

The mixed model is used to represent a DMA equations in which the branch flows and nodal heads are the unknown variables (Brdys and Ulanicki 1994). The head-flow relationship for a pipe element with an origin node i and the destination node j, is expressed by Hazen-Williams formula, equation(3.2).

For a valve element connecting node i as an origin and node j as a destination node, the following equation (5.1) holds

$$h_i - h_j = K_{ij}(v_{ij}) \cdot R_{ij} \cdot q_{ij} \cdot \left|q_{ij}\right|^{0.852} \tag{5.1}$$

Where h_i and h_j are head in [m] at node i and j, respectively. R_{ij} is the resistance of the valve element. $K_{ij}(v_{ij})$ is the resistance modification coefficient related to the valve opening v_{ij}, the fully opened valve is represented by $K_{ij}(v_{ij})$=1, and the completely closed valve is represented by a very big value theoretically equal to infinity. q_{ij} is the flow in [l/s] from node i to node j through the valve.

5.4.2 Mass balance at nodes

Equation (3.1) represents concept of the continuity (mass balance) for any node in the hydraulic network. The mass balance equation for each connection node with unknown head completes the algebraic set of the system of equation for the mixed model of the hydraulic network.

5.4.3 Leakage model

The pressure control analysis requires enhanced hydraulic model, which incorporate pressure dependent leakage terms. The leakage is usually split into background and burst components. The background leakage represents small seepages through numerous connections, joints and fittings. It depends on the operational service pressure in pipes and the purpose of the pressure control is to reduce this component.

Several mathematical models relating the leakage and the operating pressure have been proposed (Brown 2007; Giustolisi et al. 2008; Koppel et al. 2007).

The leakage-pressure relationship as shown in equation (3.16) has been assumed and added to the standard hydraulic equations to create an extended hydraulic model (Collins et al. 1978). Estimation of the parameters of the leakage model was previously described in chapter 3, section “3.4.7”.

5.5 Optimisation Problem

The aim of the optimisation problem of pressure control is to calculate the best PRV setting (the decision variables) to minimise and to smooth the pressure across the network in order to reduce the background leakage (objective function) subject to the operational constraints.

5.5.1 Objective function

The control objective is for each time step to minimise the cost of the boundary flows

$$\phi_t = \sum_{i \in I_b} c_i(t)\, q_i(t) \qquad t \in T \tag{5.2}$$

where $c_i(t)$ is the price per unit of volume including the cost of production, treatment and transport at time t. $q_i(t)$ is the source flow from boundary node i at time t. I_b is the set of boundary nodes. T is the set of time steps. Because the demands have been assumed not to be affected by the pressure, minimising the total cost of the boundary flows is equivalent to minimising the leakage flow. Pressure control methodology to reduce background leakage is traditionally applied for DMA with no storage reservoirs due to this reason, the optimisation problem has been solved independently at each time step as there is no dynamics in the system.

5.5.2 Equality constraints

Equality constraints include the hydraulic network governing equations to ensure that, all calculated variables should satisfy the hydraulic model. The equations that describe the hydraulic model with pressure dependent leakage are the equality constraints in the optimisation problem.

5.5.3 Inequality constraints

A set of operational constraints contains the requirements to ensure a feasible state of a physical system. Pressure constraints for ordinary, critical and boundary nodes are also considered to ensure minimum service pressure of 15-20 m and to avoid excessive high pressure at any node, the pressure constraints for all nodes have to be within the general operational limits $h_{i,min}$ and $h_{i,max}$

$$h_{i,\min} \le h_i \le h_{i,\max} \tag{5.3}$$

The pressure limits $h_{i,\min}, h_{i,\max}$ may depend on the node type, e.g. constraints at critical nodes are tighter than at normal connection nodes and the limits at the boundary nodes may be imposed by external conditions.

In a DMA it is useful to distinguish a set of boundary nodes I_b that are connected to external nodes (which don't belong to a DMA) through PRVs. Boundary head constraints imposed on boundary nodes representing external conditions on sources are considered. Where, the head at a boundary node, $h_{b,i}$, has to be within a possible range imposed by the external conditions.

$$h_{b,i,\min} \le h_{b,i} \le h_{b,i,\max} \tag{5.4}$$

where $h_{b,i,min}$ and $h_{b,i,max}$ are the minimum and maximum available boundary heads

The boundary flow, q_b, constraints are to determine the flow direction and to impose upper bounds of the supply flow, $q_{b,i,\max}$, at a boundary node.

$$0 \le q_{b,i} \le q_{b,i,\max} \quad i \in I_b \tag{5.5}$$

5.5.4 Decision variables

The decision variables in the formulated optimal pressure control problem are the boundary heads h_i , $i \in I_b$ representing the boundary PRV set-points and the resistance modification coefficient $K_{ij}(v_{ij})$ for the internal PRVs, equation (5.1). Subsequently, the PRV resistance is translated into the PRV set-point for the control implementation.

5.6 Time versus Flow Modulation Implementation

The optimisation problem is solved T times and provides optimal time schedules for the PRV set-points $\hat{h}_i(t), i \in I_{PRV}$, where I_{PRV} is the set of boundary and internal PRVs, the corresponding PRV optimal flows are denoted by $\hat{q}_i(t)$. The PRV can be actuated remotely or the schedules can be stored locally in individual PRVs in both cases an electronic controller is required which will adjust the set-point accordingly.

Optimal flow modulation rules can be obtained by eliminating time from the optimal solutions and producing functional relationships between the optimal heads (set-points) and the flows ('scatter plots')

$$\hat{h}_i = f_i\left(\hat{q}_{i_1}(t), \hat{q}_{i_2}(t), \ldots, \hat{q}_{i_{I_{PRV}}}(t)\right), \quad i \in I_{PRV} \tag{5.6}$$

In a general case the set-point of the *i-th* PRV depends on the flows through all PRVs. Implementation of such a strategy would require a central controller and/or communication links between all PRVs so that each PRV controller can read flow values from all other PRVs to calculate the set-point.

One can pose the question about the possibility of implementing local modulation curves, i.e. decomposition of the control law (5.6), where the set-point depends only on the local flow.

$$\hat{h}_i(t) = f_i\left(\hat{q}_i(t)\right) \tag{5.7}$$

The practical answer to this question can be obtained by plotting an individual scatter plot $\left(\hat{h}_i(t), \hat{q}_i(t)\right)$ for each PRV. If the points form a smooth curve (a functional relationship) then the individual flow modulation is possible. If they form a cloud of points i.e. for a given flow a head is not determined uniquely (lack of a functional relationship) the individual flow modulation is not possible and either time schedules or centralised flow modulations should be implemented. In this case, a forced implementation of individual modulation curves will result in significant hunting and instabilities in the WDS.

5.7 Implementation of Pressure Control Algorithm

The described optimal PRV scheduling algorithm has been embedded as a module into the Finesse software package (Rance et al. 2001), Figure 5.1. The module has been coded using the advanced mathematical modelling language known as General Algebraic Modelling System (GAMS) (Rosenthal 2007) and uses CONOPT as a non-linear programming solver (Drud 1994, 2008). More details about GAMS code and CONOPT are presented in Appendix A. The solution is in the form of schedules for the PRV set-points. In addition, the results has been post-processed and represented as a modulation curve (valve flow against optimal outlet pressure), shown in Figure 5.2.

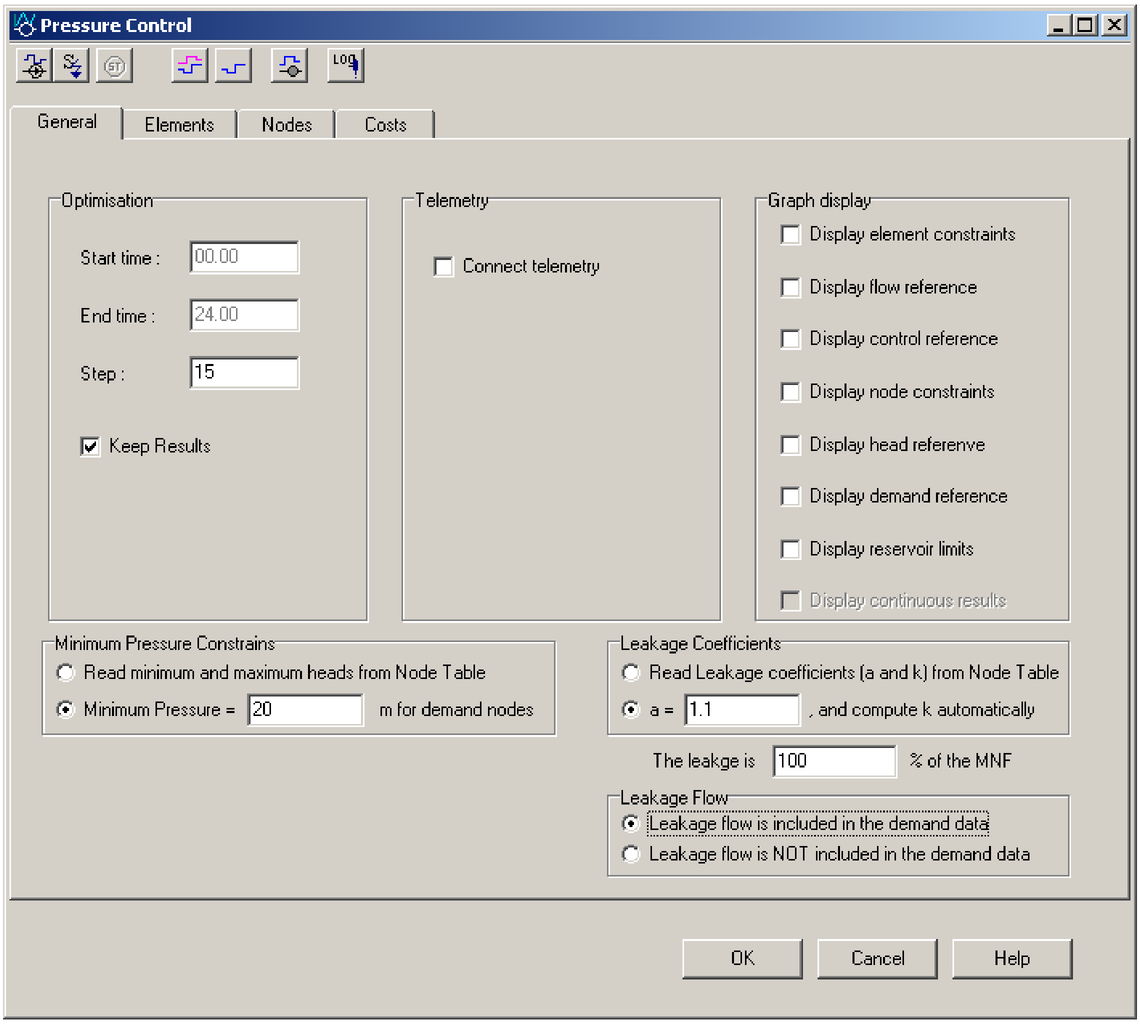


Figure 5.1 Graphic user interface of pressure control module in Finesse

The PRV scheduling algorithm can be used for off-line planning studies such as assessing the benefits of introducing the leakage management or for on-line pressure control, which may be implemented in either predictive control or feedback control as a real time control scheme (Drewa et al. 2007; Ulanicki et al. 2000). Predictive control calculates the optimal PRV schedules at each interval of time by the optimal scheduling algorithm, using updated demand prediction. The method could be considered as a time modulation scheme and requires advanced PRVs equipped with controllers that accept time profiles. The feedback control structure uses controlled PRVs by sensing its flow, in such PRVs, the outlet pressure (set-point) depends on the valve flow.

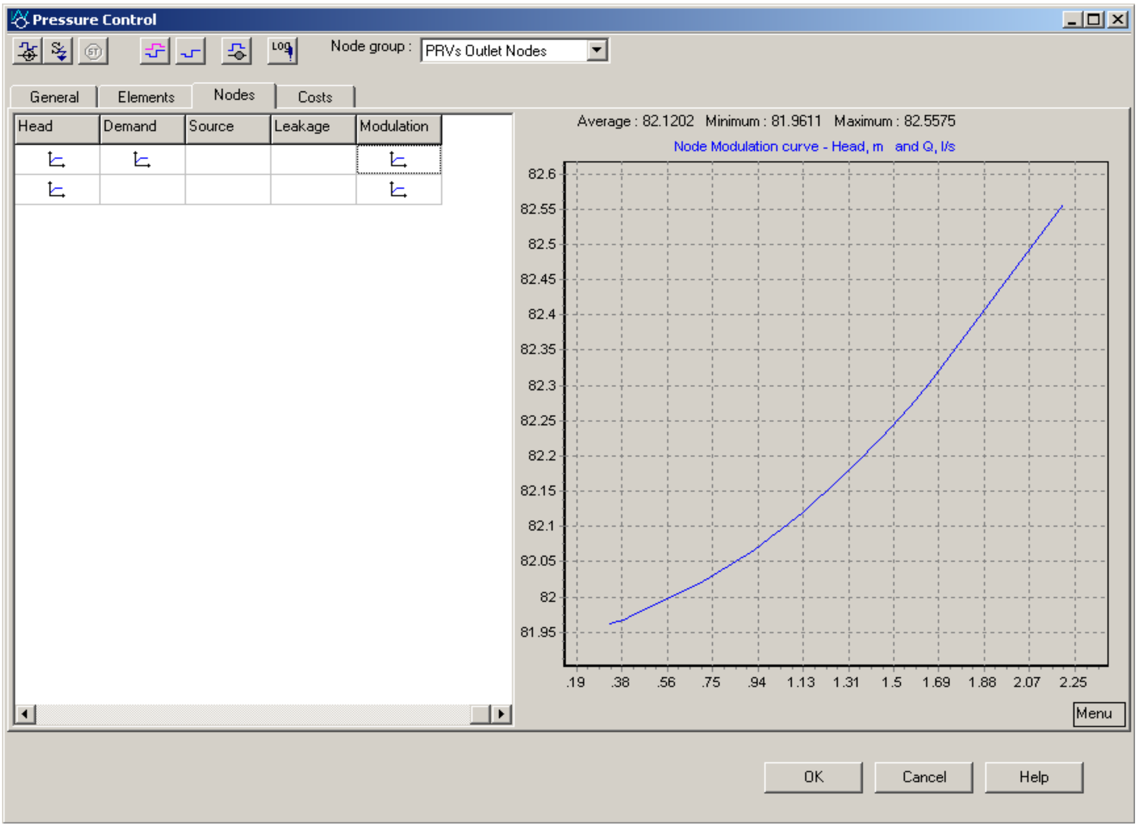


Figure 5.2 results post-processor for pressure control module in Finesse

It has been assumed that the standard information required by the hydraulic model are given together with the information about the minimum night flow and the unit prices of the boundary flows. The decision variables are the set-points for the boundary valves and resistance coefficients $K_{ij}(v_{ij})$ for the internal valves. The constraints are the network hydraulic equations and the operational constraints of the minimum and maximum pressures and boundary flows. The objective function represents the cost of the boundary flows. Finesse has been used to build the hydraulic model of the network and to define the pressure control problem, the GAMS input file has been generated and the NLP solver CONOPT has been called to solve the optimisation problem. In order to accelerate the convergence of the optimisation algorithm the initial solution has been obtained from the simulation of the current PRV settings. The hydraulic model of the network has been simulated by using the extended content model including pressure dependent leakage and has been solved by using the optimisation technique. In the following section, two case studies have been solved to assess the performance of the developed algorithm.

Pressure control module has been installed on ABB 800xA® system to be used online to compute the optimal PRV setting of different DMAs at Yorkshire water services (YWS). The module are being run on one hour basis, and by using a demand forecasting tool the demand of each node within the DMA is computed to meet the real operating conditions. Pressure control module is then computing the optimal PRV setting according to the new demand value.

5.8 Case Studies

Two different DMAs have been considered to test the developed pressure control module provided by YWS. The case study DMAs have boundary and internal PRVs to examine the functionality and reliability of the module under different model characteristics. Epanet network models and GAMS code files for both case studies are provided on the enclosed CD.

5.8.1 E067-Waterside case study

A DMA in the North Yorkshire, UK called E067-Waterside is the first case study. The zone is predominantly urban domestic/light industrial. The total mains length is 6.272 km, with 10 valves enclosing the DMA. The DMA contains two PRVs, the first, PRV1 located upstream of the inlet meter and the second, PRV2, located downstream as illustrated in Figure 5.3. The DMA contains 409 domestic and 11 commercial properties with a daily demand of 160 m^3. There are inlet flow and pressure measurement points, and a monitored pressure measurement at a critical node. DMA E067-Waterside has water supplied via the boundary inlet node, which has a variable inlet head ranging from 115 m at the maximum demand time to 135 m at the night. The total measured inflow to E067-Waterside is around 0.5 l/s during the night and increases to reach its maximum value of 3.5 l/s at 7:00 am, then decreases to the average level of 2 l/s during the day. The boundary PRV, PRV1, has been set to reduce the inlet head to 110.88 m, while the set-point of the internal PRV, PRV2 has been set to 110.05 m as provided in the hydraulic model. The hydraulic Epanet and Finesse models, GAMS code and CONOPT output result file of this case study are provided in the enclosed CD, file descriptions, paths and locations are listed in Appendix D.

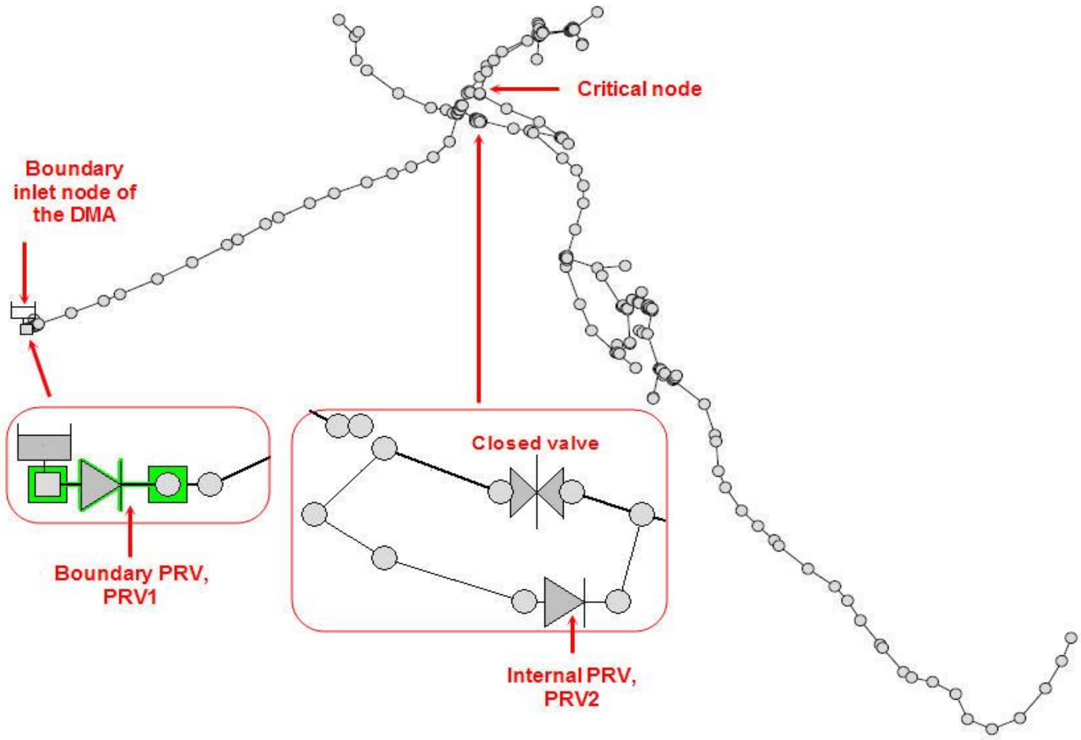


Figure 5.3. Layout of the E067 Waterside DMA

The optimal schedules for PRV1 and PRV2 set-points have been calculated using the developed module in Finesse and leakage reduction has been evaluated. The optimisation has aimed to reduce the inlet flow with pressure constraints at the critical node above 20 m. The optimal outlet head of the boundary PRV1, is approximately constant with time as depicted in Figure 5.4, and equal to 110 m, which is very close to the current setting. The optimal schedule of the outlet head of PRV2 (internal PRV) has an almost constant value of 82.5 m. The total savings in the inlet flow are 5.7% mainly due to the reduced settings of PRV2. Figure 5.5 shows the difference between the current and the optimal leakage and inlet flow to the DMA. The leakage is reduced by 0.102 l/s on average which represent 20% of the original leakage flow. The minimum pressure of 20m at the critical node has been maintained over the entire time horizon. The application of flow modulation is not necessary as the optimal PRV schedules are constant, this is due to very low head losses across the DMA.

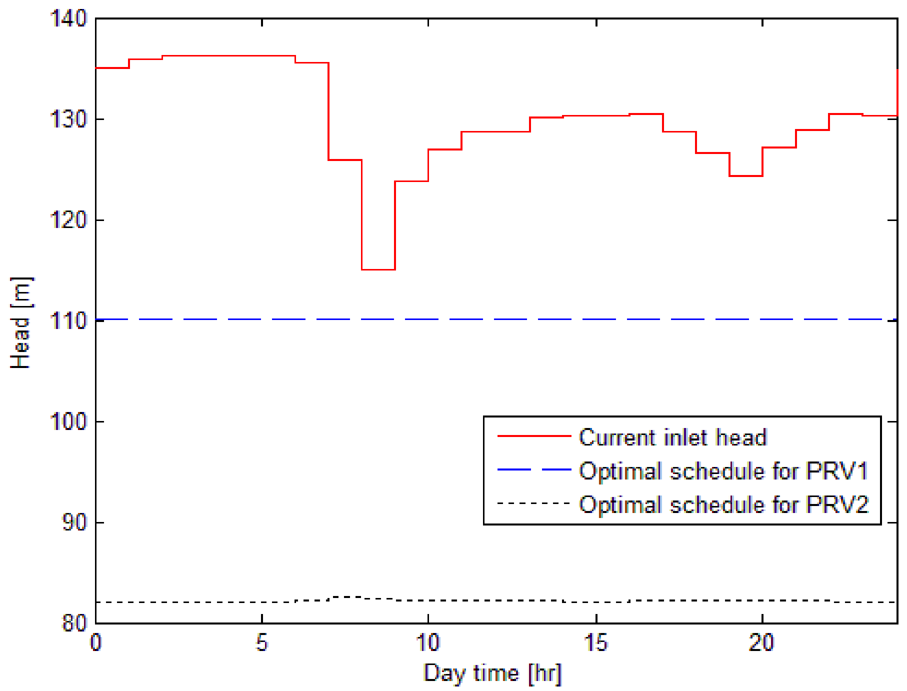


Figure 5.4. Inlet head and optimal schedules for the boundary and internal PRVs

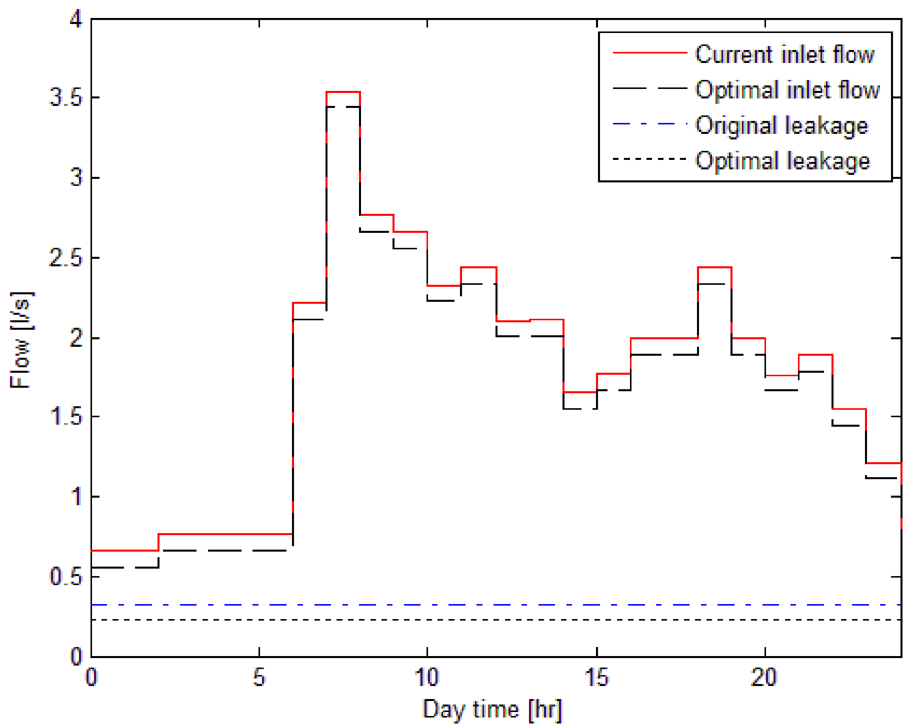


Figure 5.5. The current and optimal imported flow to the DMA and leakage

5.8.2 E093- Barrowby case study

DMA E093-Barrowby located Yorkshire, UK, is used as the second case study. The DMA has one boundary PRV and 4 internal PRVs as shown in Figure 5.6. The area contains 171 domestic properties and 42 commercial properties with a daily demand of 300 m^3. There is one inlet flow and pressure measurement point. The DMA E093 boundary head changes from 164 m at the maximum demand time during the day to 171.75 m at the night. The total measured inflow is around 1.9 l/s during the night and increases to 4.6 l/s at 7:00 am and then decreases to the average level of 3.5 l/s during the day. PRV1 is not active (fully open), while PRV2, PRV3, and PRV4 have been set to reduce the outlet head to 122.98, 105.05, and 127.8 m, respectively. The hydraulic Epanet and Finesse models, GAMS code and CONOPT output result file of this case study are provided in the enclosed CD, file descriptions, paths and locations are listed in Appendix D.

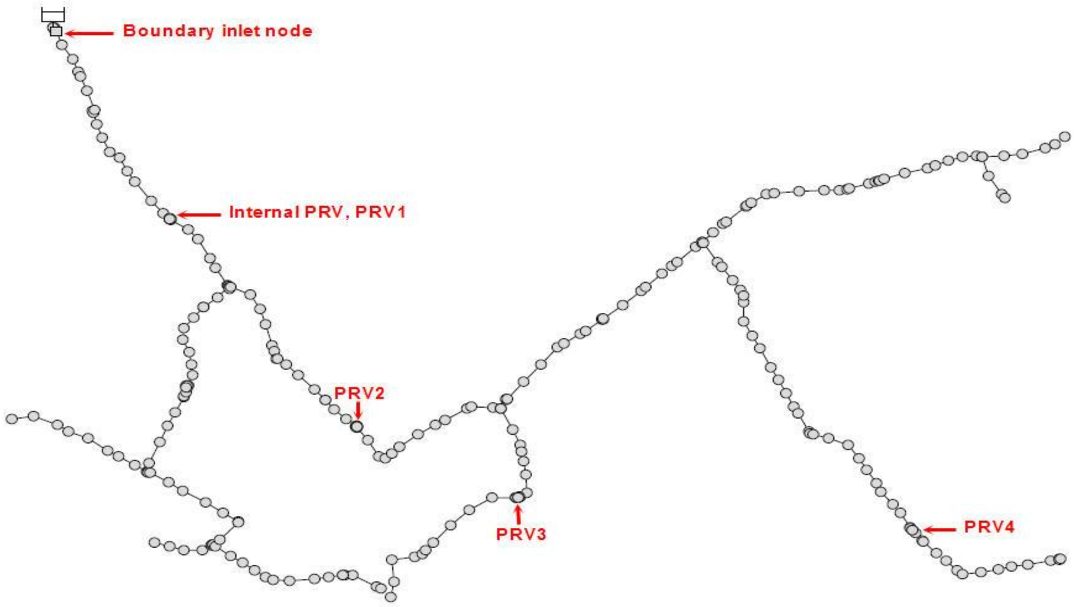


Figure 5.6. Layout of E093-Borrowby DMA

The PRVs outlet pressures have been optimised using the developed algorithm and the results are shown in Figure 5.7 where the optimal boundary head is varying from 139.5m to 143m. The optimal schedules of the internal PRVs are depicted in Figure 5.8 the optimal set-points for PRV1, PRV3, and PRV4 are almost constant with time and have the values of 140.5m, 100.5m, and 97 m, respectively.

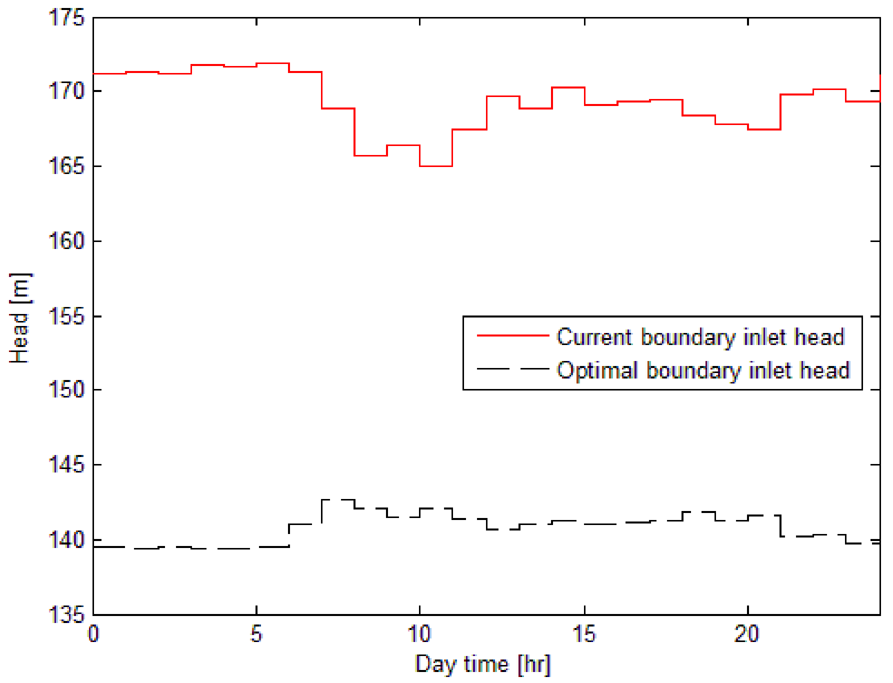


Figure 5.7. The current and optimal head of the boundary node of E063-Borrowby DMA

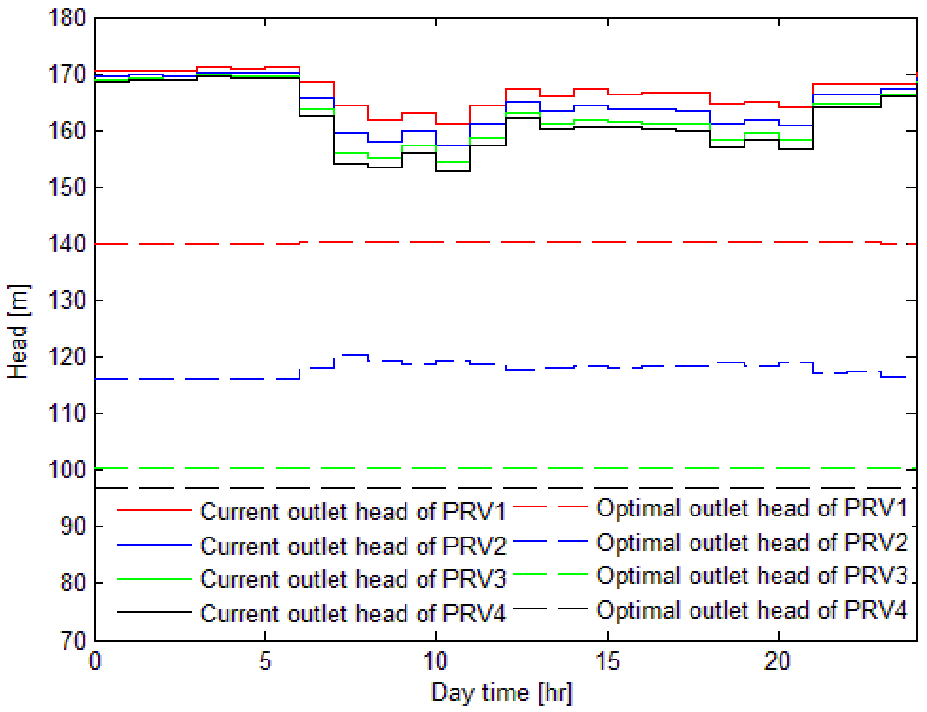


Figure 5.8. The current and optimal schedules of the internal PRVs of E063-Borrowby DMA

The PRV2 set-point varies from 116 to 120.5 m. The implementation of the optimal schedules saves 36.2 m^3/day and reduces the leakage by 45% as shown in Figure 5.10. After plotting scatter graphs for the boundary node and PRV2 shown in Figure 5.9, it appeared that they represent smooth curves and the decomposed flow modulation control can be applied in this case.

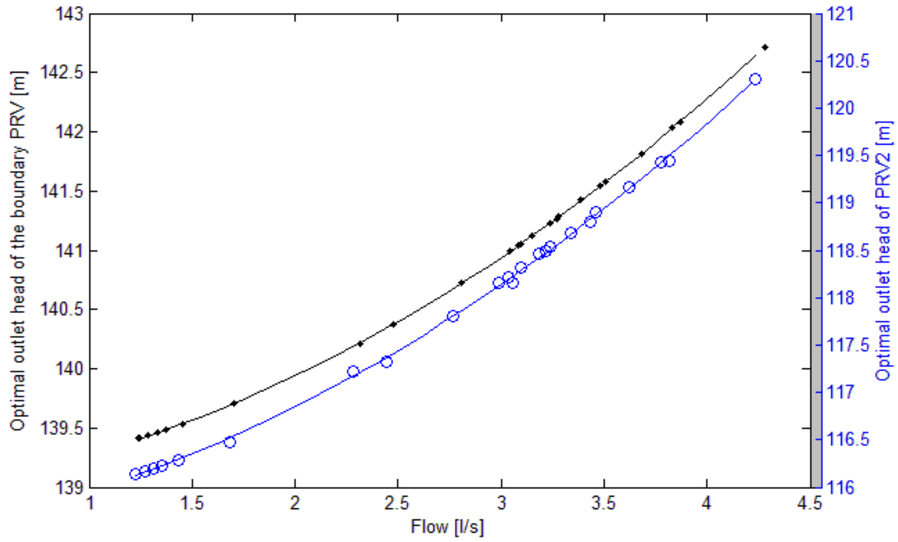


Figure 5.9. The flow modulation curves for the two PRVs

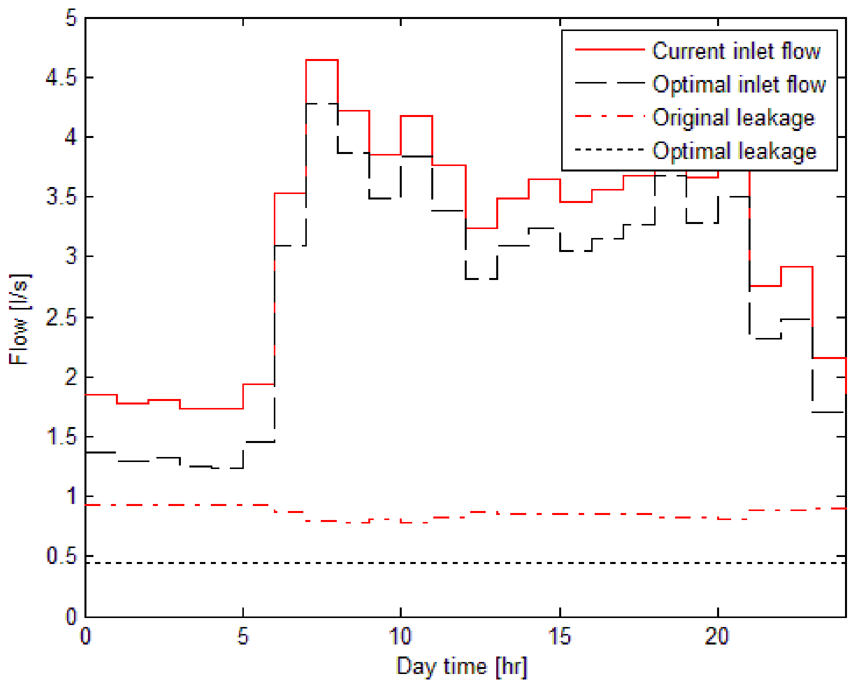


Figure 5.10. Current and optimal inlet flow to the E063-Borrowby DMA

5.9 Summary

A fast and efficient method to calculate the optimal time schedules and flow modulation curves for the boundary and internal PRVs has been presented in order to minimise the leakage in WDSs. The cost of boundary flows which include leakage flows has been minimised. An extended content model with pressure dependent leakage has been solved to provide starting point for quick convergence. The boundary and internal PRVs have been treated differently, the decision variable for a boundary valve is PRV set-point whereas for the internal valves is a valve resistance. Then, The resistance is automatically translated into a set-point for field implementation. The optimisation problem has been solved by a non-linear programming solver called CONOPT/GAMS. The program calculates time schedules for single and multi-inlet DMAs. The optimal schedules can be translated into centralised flow modulation rules where a set-point for one PRV depends on flows through all other PRVs. For weakly interacting PRVs it is possible to obtain decomposed flow modulation curves where the set-point depends only on the local flow.

The algorithm has been implemented as a module in the Finesse package and allows to solve complete pressure control tasks. A user needs to provide a hydraulic model and leakage information, at least minimum night flow in the absence of any other information.

Evaluation of optimal control strategies and benefit analysis in terms of leakage reduction for the two case studies provided by Yorkshire Water Services has been included. DMA E067-Waterside, which has a boundary and one internal PRV, has been optimised and it has been found that, the leakage can be reduced by 20%. Due to the constant optimal pressure schedules of the PRVs, the flow modulation control is not applicable in this case. In another case study, DMA E093- Borrowby, which has four internal PRVs, the leakage can be reduced by 45%. The decomposed flow modulation control can be applied on the boundary node as well on the PRV2 of the DMA E093-Borrowby.

Chapter 6

6 Pressure and Leakage Management in WDSs via Flow Modulation PRVs

In this chapter, a genetic algorithm (GA) has been used to calculate the coefficients of second order relationship between the flow and the optimal outlet pressure for a PRV. The method has been implemented in Matlab linked to the Epanet hydraulic simulator. The obtained curve can be subsequently implemented using a flow modulation controller introduced in Chapter 7.

The results of optimal PRV flow modulation via GA has been compared with the time schedule approach using a non-linear programming method described in chapter 5. The results of both techniques are very close to each other and resulted in almost the same amount of leakage reduction. The main advantage of the flow modulation in comparison to time schedules is that the modulation curve is calculated once and operates robustly over a wide range of demands. Although, the flow modulation is getting popular in the UK for single inlet DMAs, a special care must be taken for multi-inlet DMAs where interactions between inconsistent flow modulation curves may lead to resonance (hunting) phenomena. Hunting phenomena is an undesirable oscillation of appreciable magnitude, prolonged after external stimuli disappear. Sometimes called cycling or limit cycle, hunting is evidence of operation at or near the stability limit. In control valve applications, hunting would appear as an oscillation in the loading pressure to the actuator caused by instability in the control system or the valve position (FISHER 2005).

6.1 Motivation

Applying pressure management policies in order to reduce water loss and the frequency of burst pipes in WDS becomes one of the most important issues in water industry. PRV and the recent electronic and hydraulic controllers provide promising tools to apply the pressure management policy. The motivation of the current study is to develop a robust time independent optimal setting of the PRV in terms of the outlet pressure depending on the PRV flow which is call flow modulation. A local embedded hydraulic controller introduced in Chapter 7 can be employed to apply the idea of feedback controlled PRV according to the optimal flow modulation characteristics computed by the proposed algorithm. The advantages of feedback control are that the output is measured and the control takes into account unforeseen disturbances such as frictional and pressure losses. Feedback control architecture ensures the desired performance by altering the inputs immediately once deviations are observed regardless of what caused the disturbance. A feedback control system consists of five basic components: (1) input (PRV flow), (2) process being controlled (DMA), (3) output (PRV outlet pressure), (4) sensing elements (flow meter or a Pitot tube), and (5) controller and actuating devices (electronic or hydraulic controller). A final advantage of feedback control stems from the ability to track the process output and, thus, track the system's overall performance.

6.2 Problem Outline

In this section, an algorithm for the optimum flow modulation of the outlet pressure of the boundary PRVs to minimise and smooth the operational service pressure across a DMA has been introduced. This algorithm is based on calculating the optimal PRV flow modulation for given demand incorporated with the leakage model. The algorithm of the pressure control is limited to the steady state condition. This means, changes of PRV settings cause instantaneous changes of flows and heads in the network. The components of the optimal pressure control problem are the fitness function, the hydraulic model of the network taking into account the leakage model, and operational constraints.

6.3 Fitness Function

The control objective is minimising the total leakage flow

$$\phi = \sum_{t\in T}\sum_{i\in I_d} l_i(t) + \left\{ \sum_{t\in T}\sum_{i\in I_c} \Theta_i(t) \quad \text{if} \quad p_i(t) < p_{\min} \right\} \tag{6.1}$$

where, $l_i(t)$ is the leakage flow at node i. I_c is a set of critical nodes. $p_i(t)$ is the pressure of the critical node i at time t. p_{min} is the minimum allowed pressure in the system, and T is the set of time steps. The penalty terms $\Theta_i(t)$ have been added to the fitness function to ensure that the pressure at the critical nodes will not violate the minimum allowed service pressure in the system at any time and is calculated as following.

$$\Theta_i(t) = \begin{cases} 0.0 & if \quad p_i(t) \geq p_{\min} \\ 1000 \times \left(p_{\min} - p_i(t)\right) & if \quad p_i(t) < p_{\min} \end{cases} \tag{6.1}$$

6.4 Decision Variables

The decision variables in the formulated optimal pressure control problem are the coefficients *A*, *B*, and *C* of the flow modulation curve that has been used to calculate the boundary PRVs outlet head h_i, as expressed in equation(6.2), $i \in I_b$ representing the boundary PRV.

$$h_i(t) = A \cdot q_i^2(t) + B \cdot q_i(t) + C \tag{6.2}$$

The assumption for boundary PRV is not necessary valid for a DMA with multi-inlet and internal PRV. This can be explained by plotting an individual scatter plot $\left(\hat{h}_i(t), \hat{q}_i(t)\right)$ for each PRV. If the points form a smooth curve (a functional relationship) then the individual flow modulation is possible. If they form a cloud of points i.e. for a given flow a head is not determined uniquely (lack of a functional relationship) the individual flow modulation is not possible and either time schedules or centralised flow modulations should be implemented. In this case, a forced implementation of individual modulation curves will result in significant hunting and instabilities in the WDS.

6.5 GA Implementation

The described optimal algorithm has been coded in Matlab, using the provided GA toolbox (Chipperfield and Fleming 1995; MathWorks 2010) connected to Epanet 2 as hydraulic simulator. The algorithm of the optimal modulation of PRV can be used for off-line planning studies such as assessing the benefits of introducing the leakage management or for on-line pressure control, which can be implemented in feedback control as a real time control scheme (Drewa et al. 2007; Ulanicki et al. 2000). The feedback control structure uses controlled PRVs by sensing its flow, in such PRVs, the outlet pressure (set-point) depends on the valve flow.

It is assumed that the standard information required by a hydraulic model are given together with the information about the minimum night flow. The decision variables are the coefficient of the optimal flow modulation curve, A, B and C, in equation(6.2) for the boundary PRVs. The constraints are the minimum allowed pressure at the critical nodes. The fitness function represents the total leakage flow. The penalty term has been added to the fitness function to ensure the results are feasible and the pressure at the critical node is satisfying the constraints of minimum service at any value of the demand over the simulation horizon. Epanet has been used to simulate the hydraulic model of the network, the embedded GA toolbox in Matlab uses simulation results to compute the fitness function in order to find the optimal flow modulation characteristics and to check the feasibility of the proposed solution. Figure 6.1 presents a flowchart to illustrate how the fitness function is calculated.

In the following section, a case study has been solved to assess the performance of the developed algorithm. The results of the optimal flow modulation found by GA have been compared with the solution of the optimal time schedule of PRV outlet pressure obtained by NLP method described in chapter 5.

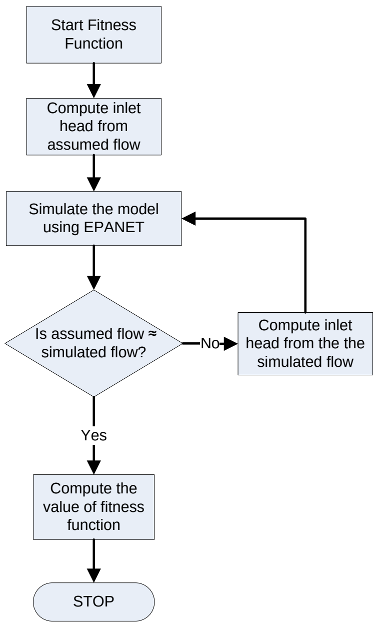


Figure 6.1 Flowchart of the module of fitness function

6.6 Case Study

6.6.1 Case study description

A016 DMA is predominantly urban domestic/industrial of total mains length 20.5 km, with a boundary PRV equipped with hydraulic controller to modulate the PRV outlet pressure according the total required flow, but the controller settings have been adjusted to keep the PRV outlet pressure constant, or the modulation has been deactivated. The topology of the hydraulic model is presented in Figure 6.2. The DMA contains 100 demand nodes with a daily demand 3.6 Ml/d of which 51% leakage (1.85 Ml/d). The DMA has water supplied via the boundary PRV, which has a constant outlet head of 93.0 m. The imported flow has a minimum value of 23.7 l/s at 04:00 am and increases to reach its maximum value of 54.2 l/s at 9:00 am, then decreases to the average level of 42 l/s during the day, as depicted in Figure 6.3. The hydraulic Epanet and Finesse models, GAMS code and CONOPT output result file of this case study are provided in the enclosed CD, file descriptions, paths and locations are listed in Appendix D.

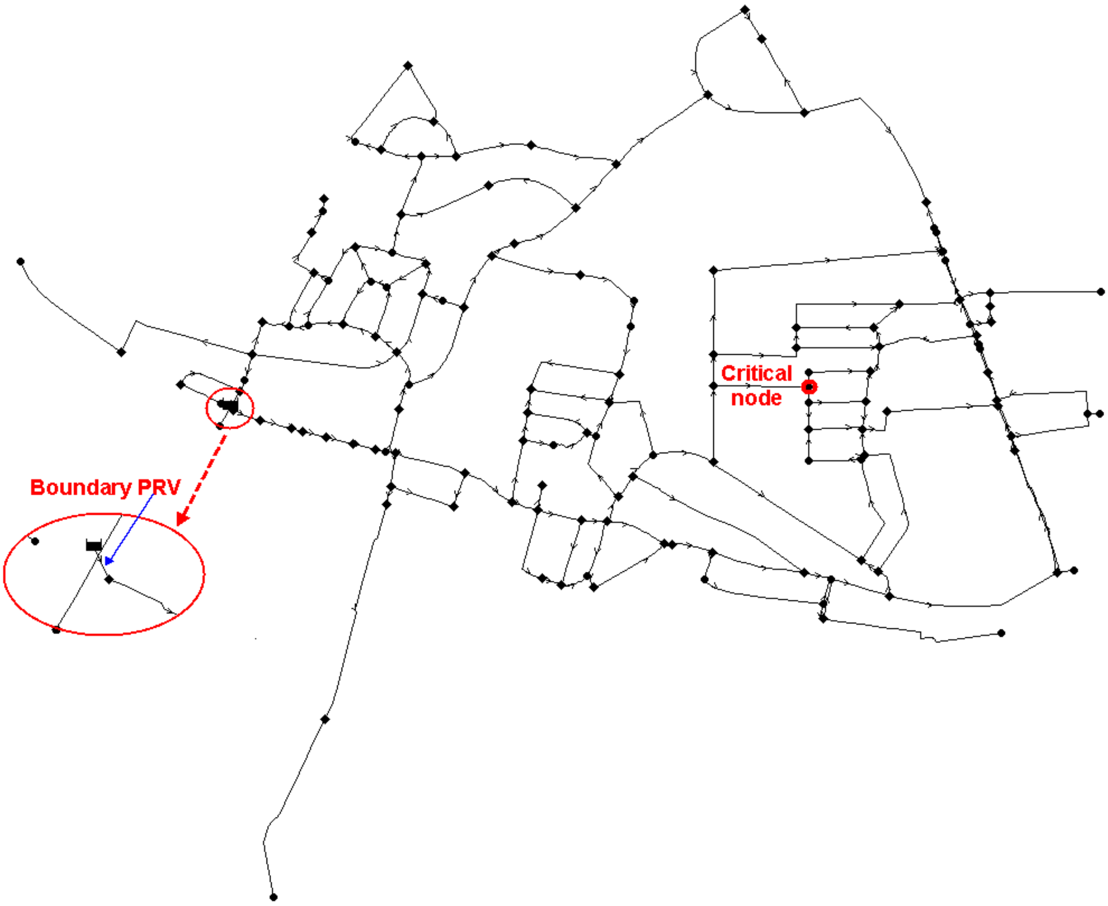


Figure 6.2 The hydraulic model of DMA a016

The optimal flow modulation curve for the boundary PRV of the DMA A016 has been calculated using GA, also the optimal time schedule of the inlet head has been obtained using the pressure control module in Finesse based on NLP algorithm described in chapter 5. Leakage reduction rates for both solutions have been evaluated. The optimisation aims to reduce the inlet flow with pressure constraints at the critical node above 20 m. In the DMA A016, the critical node with demand has been selected at the highest elevation of 59m.

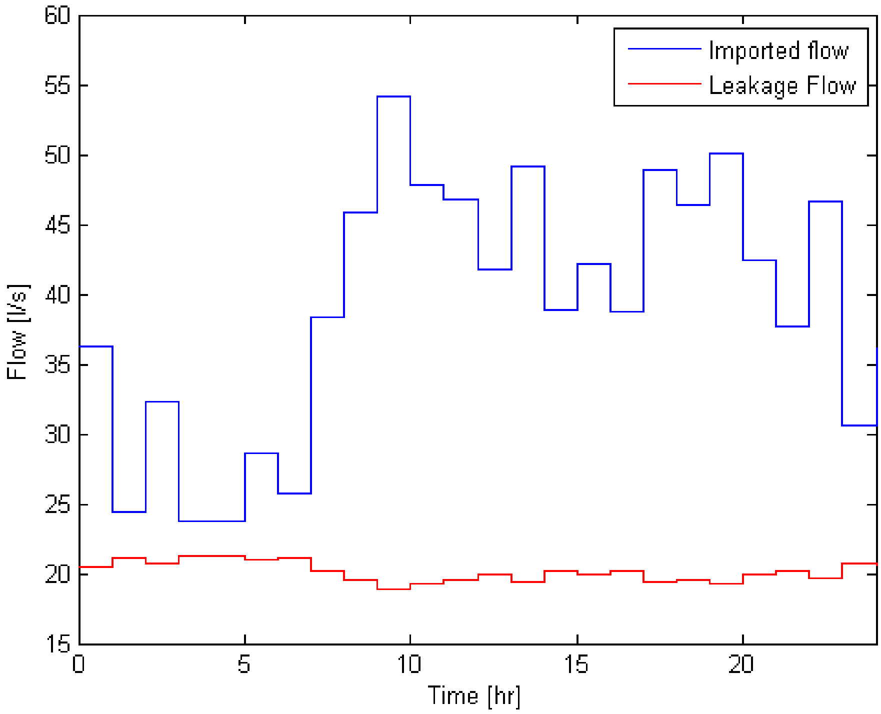


Figure 6.3 Total imported flow and total leakage flow of the DMA A0116

6.6.2 Results and discussion

GA created 51 generation to reach the optimal characteristics of the flow modulation curve for the boundary PRV, each generation contains 50 chromosomes (populations size) with 25% a migration fraction. Figure 6.4 shows the best and mean values of the fitness function of the population at every generation. The optimal flow modulation curve is given by the following equation

$$h_i(t) = 365.26\times10^{-6}\cdot q_i^2(t) + 192.75\times10^{-3}\cdot q_i(t) + 75.69$$

where, $h_i(t)$ is the PRV outlet head in [m] and $q_i(t)$ is the PRV flow in [l/s].

NLP algorithm implemented in chapter 5 has also been applied to the same case study in order to find the optimal time schedule of the PRV outlet head. The results of both techniques are discussed and compared, Table 6.1 summarises the total leakage and the leakage reduction in m^3/day and as a percent of the original leakage. It is clear that, both techniques give almost the same results in terms of leakage reduction.

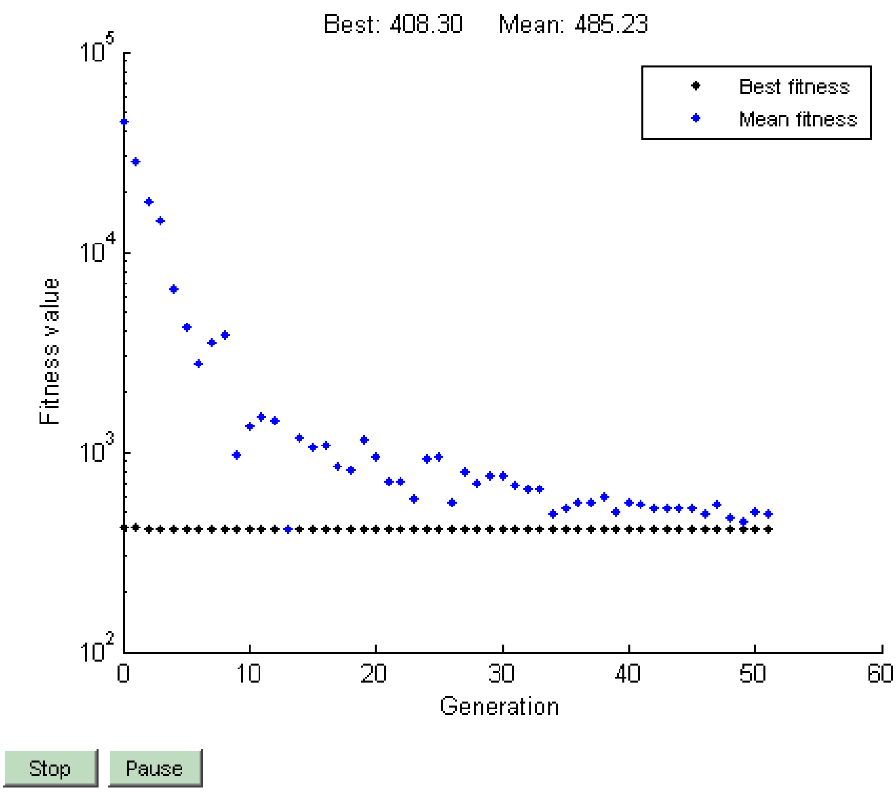


Figure 6.4 GA solution progress

Table 6.1 Leakage data for GA and NLP

	GA	NLP
Total leakage [m^3/day]	1501	1472
Leakage reduction [m^3/day]	349	378
Leakage reduction [%]	18.86	20.44

The optimal modulation curve is depicted in Figure 6.5. The minimum head of 80 m corresponds to the minimum night flow of 18.2 l/s, and then it increases linearly as the demand increase to reach the maximum value of 86.6 m at the peak demand of 51.8 l/s. Figure 6.6 illustrates the optimal time schedule of the PRV outlet pressure resulted.

Figure 6.7 shows the difference between the current and the optimal inlet flow to the DMA, which is 4.2 l/s on average. The minimum pressure of 20m at the critical point is maintained over the entire time horizon, as shown in Figure 6.8. In order to obtain the maximum benefits from the hydraulic controller, it is important to adjust the minimum and maximum outlet head of the PRV according to the provided flow modulation curve as depicted in Figure 6.5.

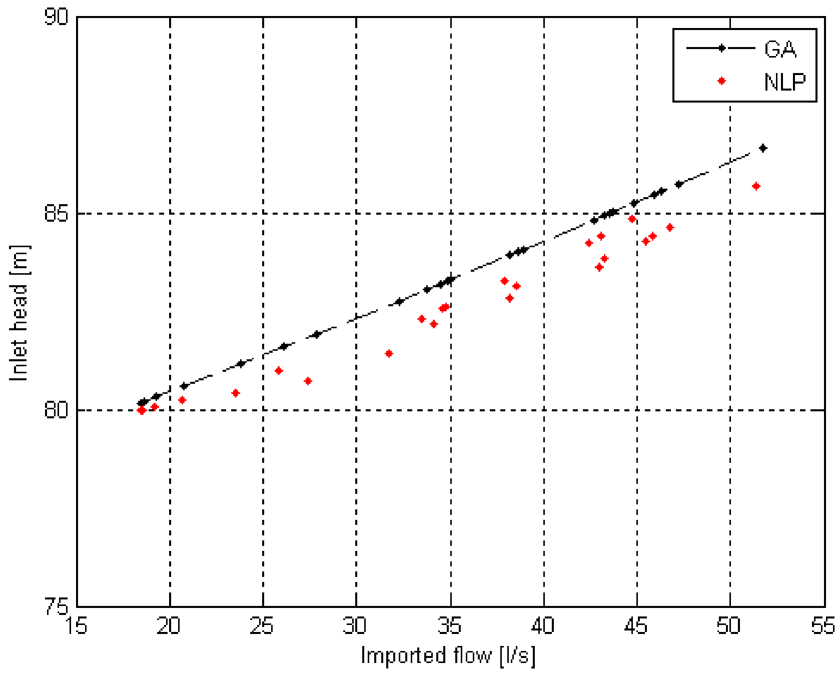


Figure 6.5 Optimal modulation curves obtained from GA and NLP techniques

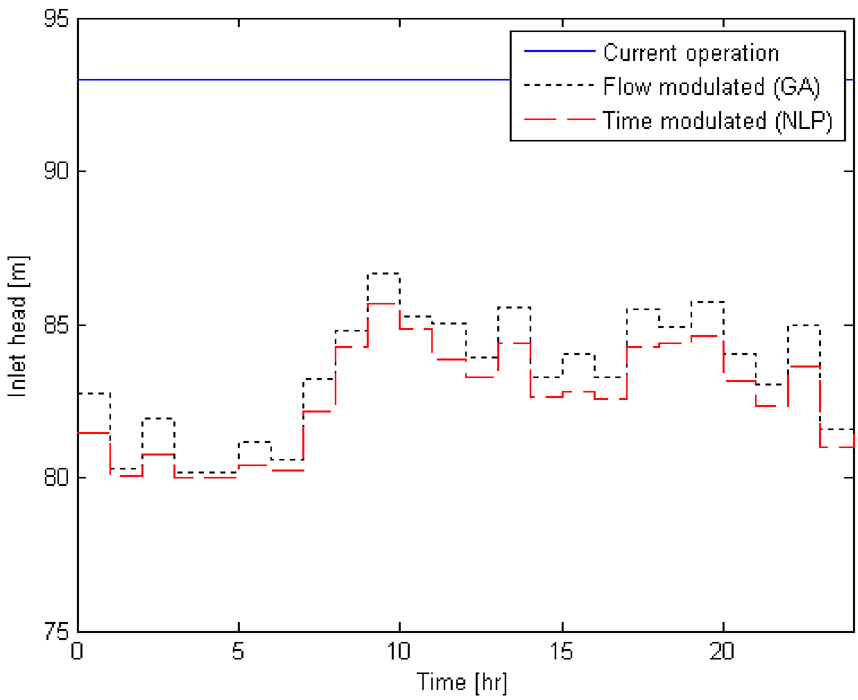


Figure 6.6 The current and the optimal schedules of PRV outlet head obtained from GA and NLP

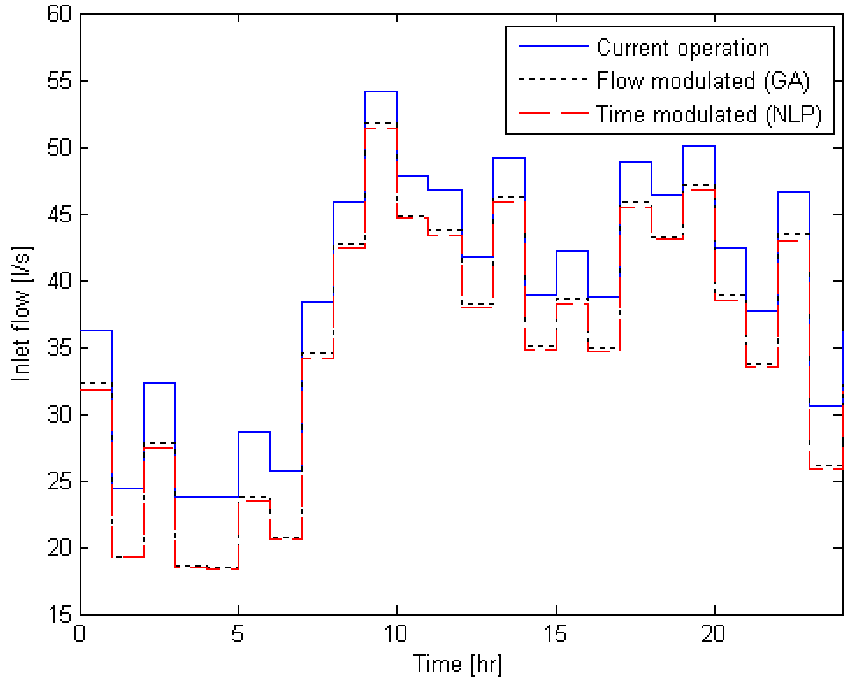


Figure 6.7 The current and the optimal imported flow obtained from GA and NLP

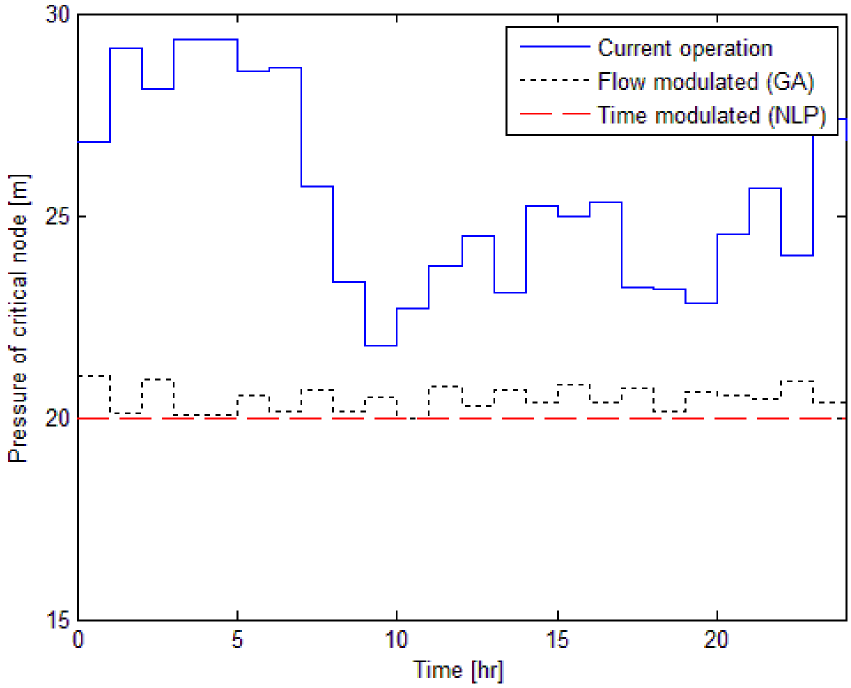


Figure 6.8 The current and the optimal critical node pressure

6.6.3 Summary

The benefits of applying pressure control policy in WDS in order to reduce the leakage have been discussed. The pressure management via flow modulation has been applied and its benefits have been documented. Flow modulation PRVs can be operated either hydraulically or electronically to modulate the outlet pressure according to the demand level and required pressure at critical nodes.

GA has been used to derive the optimal coefficients of a second order relationship between the flow and the outlet pressure for a PRV. The method has been implemented in Matlab linked to the Epanet hydraulic simulator. The obtained curve can be subsequently implemented using a flow modulation controller in a feedback control scheme.

The results of optimal PRV flow modulation via GA has been compared with the time schedule approach using a non-linear programming method described in chapter 5. The results of both techniques are very close and resulted in almost the same amount of leakage reduction. The main advantage of the flow modulation in comparison to time schedules is that the modulation curve is calculated once and can be used over a wide range of demand. The performed evaluation of optimal control strategies for the DMA A016, which has one boundary PRV, indicates that the leakage can be reduced by up to 18.8% of its original value.

Chapter 7

7 Embedded Hydraulic Controller for Pressure Reducing Valve

This Chapter describes a development of mathematical models, which represent static and dynamic properties of the AQUAI-MOD® hydraulic controller coupled with a standard PRV as well as a new experimental setup for testing the controller, for calibrating and validating the models. The purpose of the AQUAI-MOD® controller is to modulate the PRV outlet pressure according to the valve flow. The controller was experimentally tested to assess its operation in different conditions and operating ranges and in all cases showed a good performance. The mathematical models of the PRV and its controller have been developed and solved using the Mathematica software package to represent both steady state and dynamics conditions. The numerical results of simulation of the mathematical model have been compared with experimental data and showed a good agreement in the magnitude and trends. The model can be used to simulate the behaviour of the PRV and the AQUAI-MOD® hydraulic controller in typical network applications. It can also be used at the design stage to size the controller components and to compute the required set-points for the minimum and the maximum pressure before installing the controller in the field.

7.1 Introduction

Water utilities use pressure control to reduce background leakage and incidence of pipe bursts. Significant savings can often be made and there are many examples where the application of pressure control has been extremely successful (Çakmakcı et al. 2007; Girard and Stewart 2007; Marunga et al. 2006; Rogers 2005; Yates and MacDonald 2007). The control is usually implemented across DMAs that are supplied through PRVs and closed at all other boundaries (Alonso et al. 2000; Prescott et al. 2005; Ulanicki et al. 2000). Single-feed PRV schemes are often adopted for ease of control and monitoring but risk supply interruption in the event of failure. Multi-feed systems improve security of the supply but are more complex and incur the risk of PRV interactions leading to instability (Prescott and Ulanicki 2004; Ulanicki et al. 2000).

PRV can be a fixed set-point, dual (time or flow) set-point, or fully modulated. A fixed set-point PRV is a standard PRV that regulates a high, varying upstream pressure to a lower fixed and stable downstream pressure, regardless of variations in demand. The set-point of the fixed outlet PRV is manually set so that the pressure at the critical node is higher than the minimum value as required by the local regulations. Dual set-point PRV regulates the outlet pressure to two different values according to the time of the day or the demand. The high set-point is selected in the same manner as in the fixed set-point PRV, while the lower setting point is adjusted considering the lower system friction losses correlating to the low demand. The application of this valve achieves better leakage reduction compared with the fixed set-point PRV. However, the pressure at the critical node may still be too high if the demand is lower than the maximum demand but not sufficiently low to switch to the low pressure setting. Therefore, the classical usage for dual set-point PRV would be in locations where there is a distinct difference between the normal demand and the low demand, such as in a case of a PRV supplying a DMA with normal domestic demand and a single large industrial customer which causes a significant flow increase. The fully modulated PRV regulates the outlet pressure to varying set-points, so that the pressure at the critical node remains fixed at the minimum allowed pressure and stable regardless of friction losses variations due to demand. The set-points can be modulated according to either demand, time of the day, or current value of pressure at the critical node, which is sent via telemetry system to the PRV controller. This type of operation enables a maximum optimization of leakage reduction, with the best level of customer service, as the pressure is kept stable regardless of demand variations. Fully modulated PRVs are usually controlled by an electronic controller that monitors the pressures and/or the demand flow and modifies the set-point of the pilot valve of a standard PRV.

During implementation of a pressure control scheme, both steady state and dynamic aspects should be considered (Brunone and Morelli 1999; Prescott and Ulanicki 2003; Prescott and Ulanicki 2008; Ulanicki et al. 2000). The steady state aspects ensure that PRV set-points are changed according to the demand to minimise background leakage and to satisfy the minimum required pressure at the critical nodes. The dynamic aspect considers preventing excessive pressure hunting (oscillations) across a network caused by interactions between modulating valves and dynamics in a water network. A better understanding of the dynamics of PRVs and networks will lead to improved control strategies and reduced instabilities and leakage. Dynamic models are currently available for representing behaviour of most water network components. Such models are relatively simple, accurate and can be easily solved (Andersen and Powell 1999; Brunone and Morelli 1999; Pérez et al. 1993). In (Prescott and Ulanicki 2003) PRV dynamic phenomenological, behavioural and linear models to represent dynamic and transient behaviour of PRVs were developed, while in (Prescott and Ulanicki 2008) a model to investigate the interaction between PRVs and water network transients was described; transient pipe network models incorporating random demand were combined with a behavioural PRV model to demonstrate that sudden changes in the system demand can produce large and persistent pressure variations, similar to those seen in practical experiments.

The pressure control is more efficient if there is a possibility of automatically adjusting a set-point of a PRV according to the PRV flow - so called flow modulation. The PRV set-point can be adjusted electronically or hydraulically. The former requires the use of a flow sensor, a microcontroller and solenoid valves acting as actuators. The major disadvantage of this solution is the necessity of providing electrical power supply and the exposure of the electronic equipment to harsh field conditions. A hydraulic flow modulator is a simpler solution and is considered to be more robust than an electronic controller. The AQUAI-MOD® hydraulic controller manufactured by the Aquavent company (Peterborough, UK) is probably the first hydraulic flow modulator available in the market.

The AQUAI-MOD® hydraulic controller can be used to implement optimal pressure control strategies which have been developed earlier and described in chapters 5 and 6 by modulating the outlet pressure of the PRVs according to the flow. Such an approach minimises continuous over pressurisation and stress on the mains which extends infrastructure life, and therefore reduces leakage and subsequently reduces energy consumption by pumping smaller volume of water (Colombo and Karney 2009; Thornton and Lambert 2007).

The main aim of this work is to develop a detailed mathematical model of the PRV coupled with AQUAI-MOD® hydraulic controller based on phenomenological concept of each element of the system. Such a model can be used to improve the design and the mechanical construction of the controller, to resize its components, improve its robustness and functionality and to better understand the dynamics of the system to prevent the valve hunting. Another important aim of this work is to show what modelling approach and applications were used, in order to facilitate other authors developing mathematical models of similar systems.

7.2 Description of the AQUAI-MOD® hydraulic controller

The AQUAI-MOD® hydraulic controller consists of three main chambers separated by rolling diaphragms, as shown in Figure 7.1. The first is the Pitot chamber, which is connected to the Pitot tube at the outlet of the PRV. The second is the control chamber, which is connected to the inlet and the control space of the PRV through T-junction (*t1*). The pipe connecting the valve inlet and T-junction, *t1*, has a fixed orifice. The third is the jet chamber, which is connected to the outlet of the PRV. The jet chamber is also connected to the Pitot tube through T-junction *t2*. The control chamber is connected to the jet chamber by a hollow shaft (the modulating shaft), which allows the flow from control chamber to jet chamber through the discharge outlet of the jet. The flow through the modulating shaft depends on the gap (x_r) between the jet exit and the seat of the pilot shaft, these arrangements work like in a pilot valve of a standard PRV (Prescott and Ulanicki 2003). Note that the control chamber has a constant volume while the volume of the Pitot and jet chambers depends on the position of the modulating shaft connected to rolling diaphragms.

The controller modulates the outlet pressure of the PRV according to the main flow, which is sensed and converted to dynamic pressure by the Pitot tube. Standard installation of the controller requires definition of two set-points. The first one is the “minimum pressure setting” (corresponding to the minimum night flow), which is adjusted by turning the main pressure adjuster which changes the initial tension of spring 2. The working principle of this part is similar to that of a traditional pilot valve in a standard PRV. The second set-point is for the “maximum pressure setting” (corresponding to the peak demand) which can be set by changing the opening of the modulation adjuster (one directional flow needle valve). If modulation adjuster valve is fully open, there is no flow modulation and the controller acts as a standard PRV pilot valve.

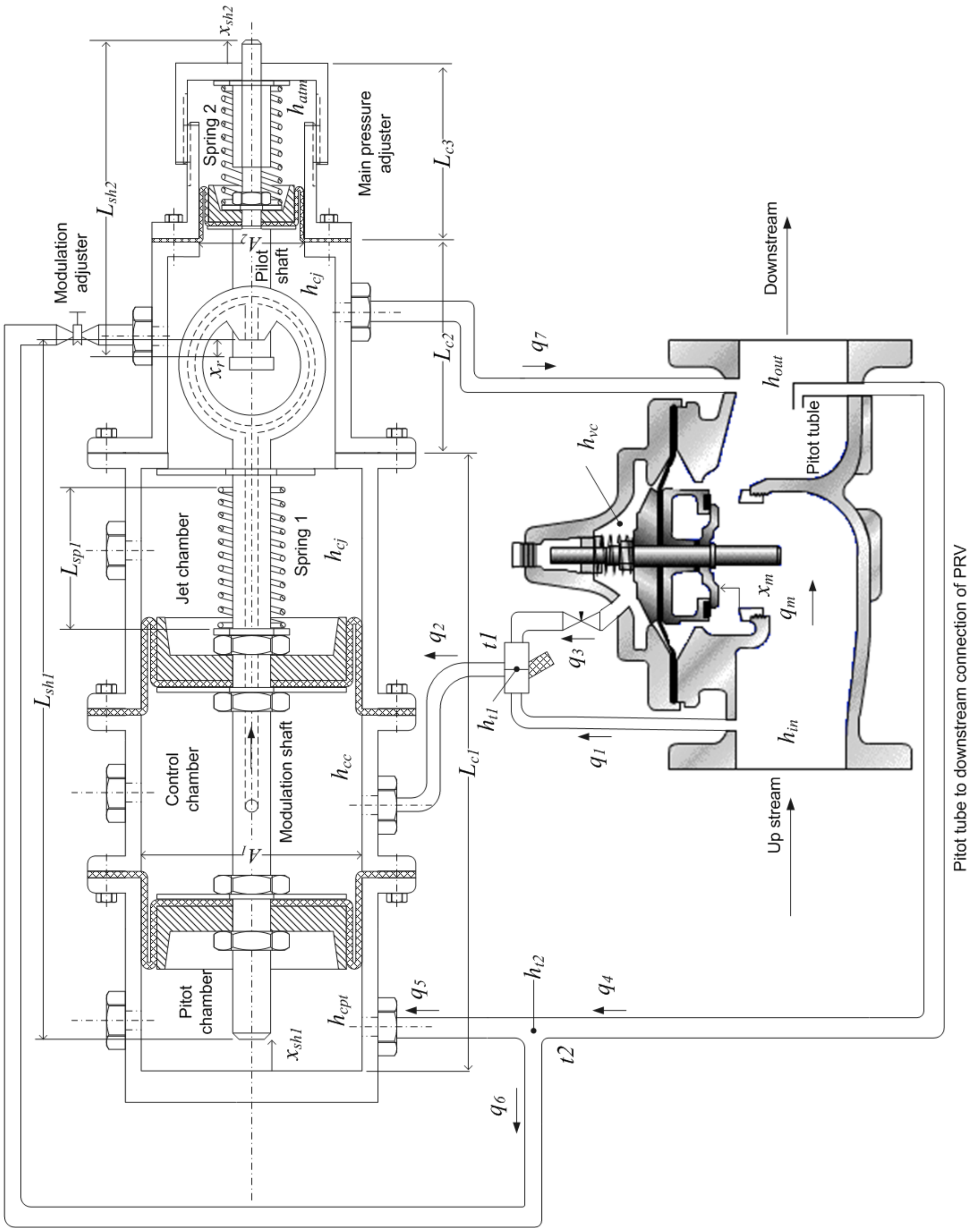


Figure 7.1. AQUAI-MOD® controller ant its connection to PRV (Patents Pending GB 0711413.5, Int'l PCT/GB2008/050445)

7.3 Laboratory Studies

In this section the descriptions of the test rig, the experiments and the results of testing the PRV and the hydraulic controller in different operating conditions are presented. The experiments were performed in a physical test-rig where the controller and the PRV could be subjected to a wider range of operating conditions than those that could be achieved in a real network without affecting the customers. The system comprising a PRV and the hydraulic controller was tested to assess and to evaluate the functionality and robustness of the system, evaluate its performance under a wide range of steady state and dynamic operating conditions, and also to use the experimental data to validate the developed mathematical model.

7.3.1 Test rig description

The design criterions for the experiment setup takes into account the environmental consideration by using a closed hydraulic loop test rig, which allows continuous flow running to avoid water loss. The schematic diagram of the test rig is depicted in Figure 7.2. A centrifugal pump of 70 m maximum deliverable head and maximum flow of 17 l/s with corresponding head of 20 m, derived by fixed speed motor, delivers the water from the tank through 3” stainless steel pipe expanded to 4” pipe before the fitting of the gate valve. The hydraulic loop has two gate valves and a Cla-val NGE9001 PRV controlled by AQUAI-MOD® hydraulic controller. The first gate valve is upstream of the PRV and is used to control the PRV inlet pressure, while the second gate valve is downstream the PRV and used to control the required flow, which represent the demand. The 4” stainless steel pipe connects the upstream gate valve, the PRV, the downstream gate valve and finally exits to the tank.

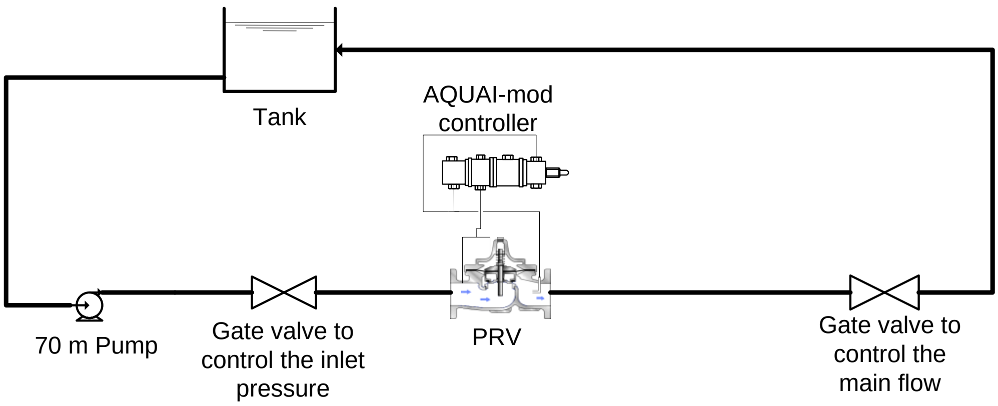


Figure 7.2. Schematic diagram of the test rig

Figure 7.3 depicts the detailed instrumentation drawing of the test rig and shows the position of each sensor and its connection to the data acquisition card. The test rig was equipped with two electromagnetic flow meters. One is a high-flow range flowmeter to measure the main flow and another is a low-flow range flowmeter, which was installed in different positions according to the needs to measure the flow from T-junction (*t1*) to the control chamber of the controller (Position 1) or to measure the flow through the modulation adjuster (Position 2). Additionally, seven pressure transducers were installed to measure the inlet and outlet pressures of the PRV, the pressures in the Pitot, control, and jet chambers of the controller, the pressure in the control space of the PRV and finally the pressure at T-junction (*t1*). A linear variable differential transformer was installed to measure the displacement of the modulating shaft of the controller. All transducers have 4-20 mA output signals to prevent electro-magnetic interference, and the main flowmeter was connected via RS232C link to the monitoring computer, the technical specifications of the transducers and flow meters are presented in Table 7.1. In order to automate the data collection, an NI 9203 series data acquisition card (DAQ) with 16 high-accuracy analogue input channels, was used to collect different signals from the measurement transducers. A LabView based data acquisition software was installed on the laptop to monitor and record 10 samples of the acquired signals per second in Comma-Separated Values (CSV) format.

Table 7.1. Sensors specification and accuracies of the sensors and transducers

Sensor	Specifications
Electromagnetic Flowmeter	MagMaster – Water & Waste Water Version SS/MAG/WW Analog output accuracy < ±0.008mA Temperature effect Transmitter <±0.08% of reading/10°C, Analog output accuracy <±0.08% of reading/10°C Power supply variation Negligible Pressure effect <0.15% over the operating range of the equipment From: ABB, website : www.abb.com
Low-range flow meter	FMG230-NPT series flow meter. Range 0.0025 - 0.633 l/s , O/P 4-20mA, accuracy 1% and hysteresis 6.25%. From: OMEGA Engineering, INC, website: www.omega.com
Pressure Transducers	642R series pressure transmitter. Range 0-10 bar, O/P 4-20mA (2 wire), accuracy < 0.25%, with G1/4" BSP male process connection, and M12 electrical connector. Power supply 10-32 v DC. From: Omni Instruments, website: www.omniinstruments.co.uk
LVDT Transducers	Industrial LVDT Series AML/IEI+/-12.5. Stroke range: ±12.5mm, O/P 4-20mA (3 wire), Non-Linearity: ±0.50%. From: Applied Measurements Limited, website: www.appmeas.co.uk

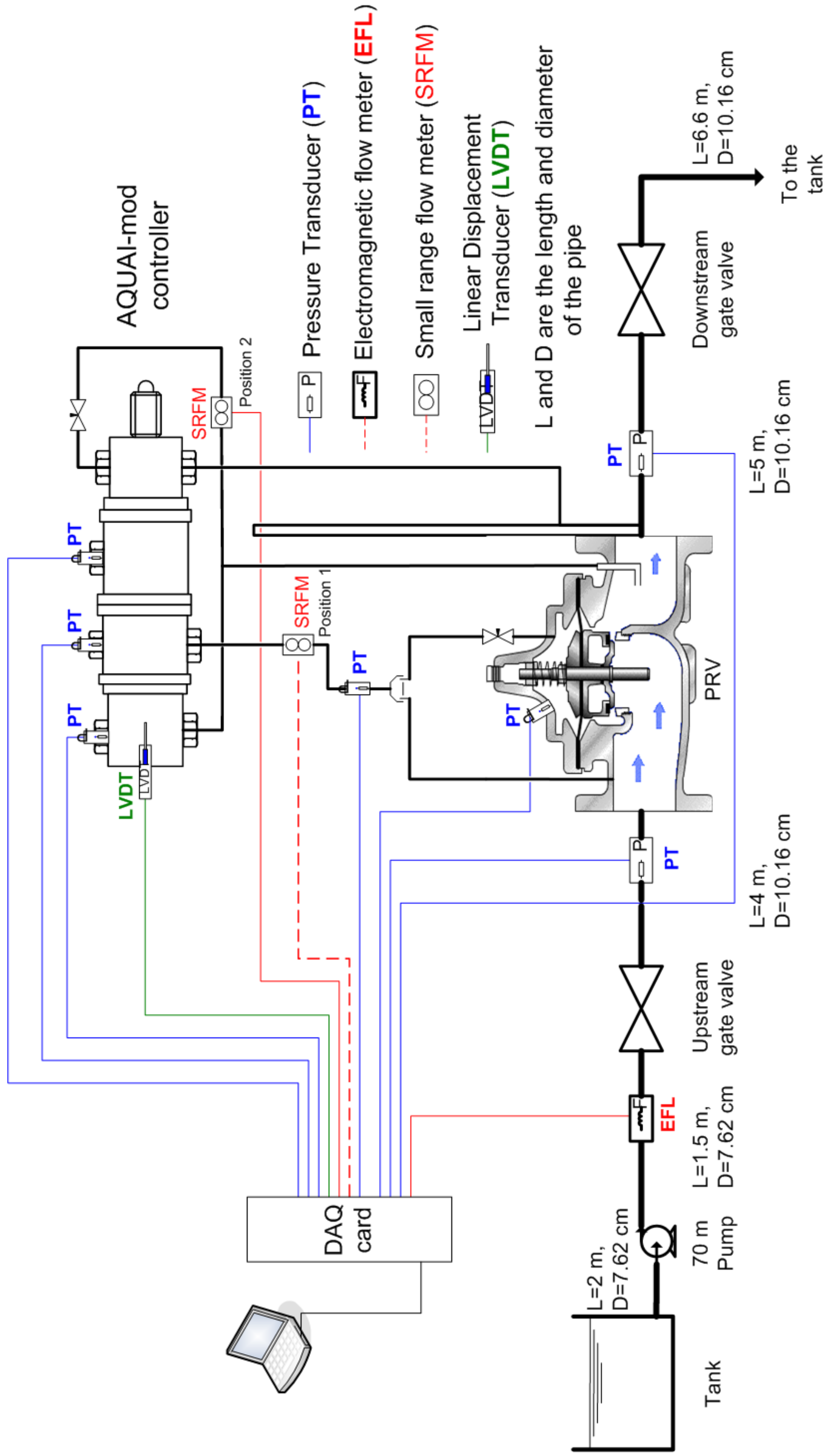


Figure 7.3. AQUAI-MOD hydraulic controller experiment layout

7.3.2 Testing behaviour of the PRV with the controller in different operating conditions

7.3.2.1 Measuring flow modulation characteristic (test 1)

Using the main pressure adjuster of the controller, the minimum outlet pressure was set to 26 m. Measurements were carried out for different modulation adjuster settings from 0% to 80% in 10% steps. For each modulation adjuster setting the downstream gate valve opening was changed (according to the sequence 6, 5, 4, 3, 2.5, 2, 1.5, 1, 1.5, 2, 2.5, 3, 4, 5, 6 turns from the complete closure), so that the main flow varied over the range from 1.75 to 17 l/s. Between each change of the downstream gate valve setting sufficient time was allowed (between 1 and 2 minutes) for the controller and the PRV to reach the steady-state conditions. Figure 7.4 shows the effect of the flow changes on the outlet pressure of the PRV. The flow and PRV inlet pressure are changing in a way similar to real operation of a WDS, when the flow decreases the pressure increases and vice versa. When the flow ranged from 15 l/s to 17 l/s, the inlet pressure was too low due to the pump characteristics therefore the PRV outlet pressure was not modulated and was lower than the inlet pressure due to the friction losses in the valve. When the flow ranged from 1.75 l/s to 15 l/s the PRV outlet pressure was modulated according to the flow between the minimum and maximum setting of the controller; as the flow decreases the PRV outlet pressure decreases and vice versa. The measurements of the PRV coupled to the controller did not show any significant dynamic effects on the PRV outlet pressure due to the flow changes.

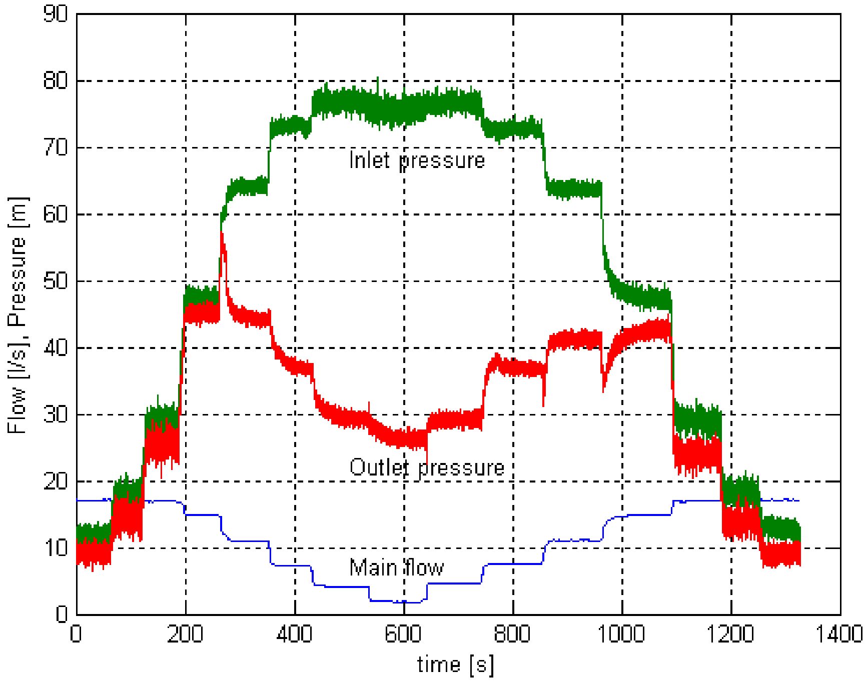


Figure 7.4. Flow modulation of the PRV outlet pressure in a typical operating condition.

7.3.2.2 Changes of modulation adjuster setting (test 2)

Opening of the modulation adjuster valve was changed according to the sequence 25%, 30%, 40%, 50%, 60%, 70%, and 80%. Between each change of modulation adjuster setting sufficient time was allowed (between 1 and 2 minutes) for the system to reach the steady-state conditions. Figure 7.5 depicts the effect of modulation adjuster setting on the PRV outlet pressure. As the opening of modulation adjuster valve increases the PRV outlet pressure decreases, which provides flexible controller setting of the PRV maximum outlet pressure to fit a wide range of operating condition and demand patterns.

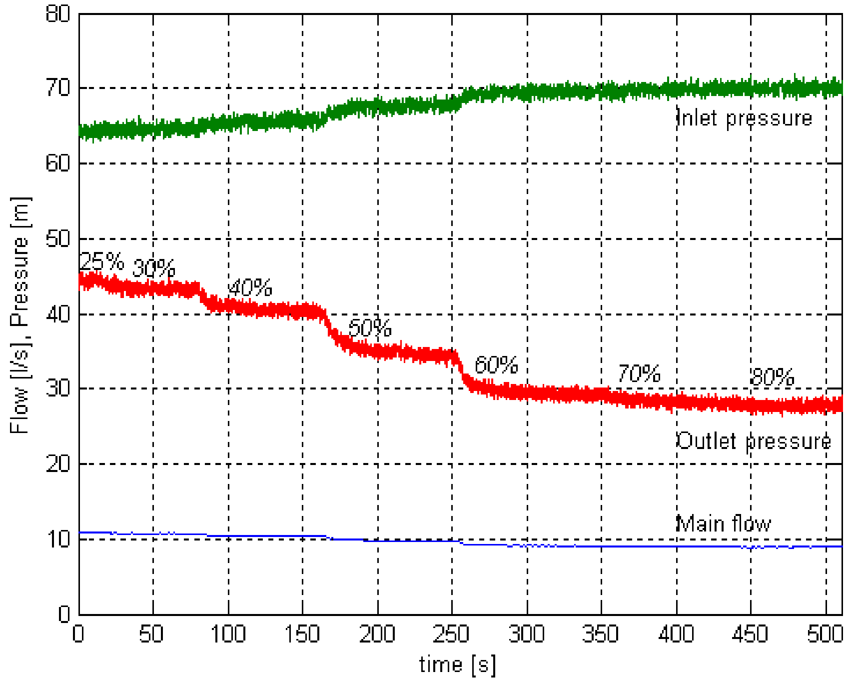


Figure 7.5. Effect of modulation adjuster setting of the controller on the PRV outlet pressure

7.3.2.3 Changes of the main pressure adjuster setting (test 3)

With the modulation adjuster set at 30%, the minimum outlet pressure was changed every minute via turning the main pressure adjuster (1 turn at a time). This was performed starting from the highest pressure setting towards the lowest pressure setting. Figure 7.6 illustrates the effect of main pressure adjuster setting, denoted N_{mpadj}, on the PRV outlet pressure. Changing the setting from 1 to 3 turns of the main pressure adjuster had no effect on the PRV outlet pressure, however changing the setting from 4 to 8 turns decreased the PRV outlet pressure by 12 m per turn, which gives flexibility for the PRV minimum pressure setting to cope with different DMA characteristics and operating conditions.

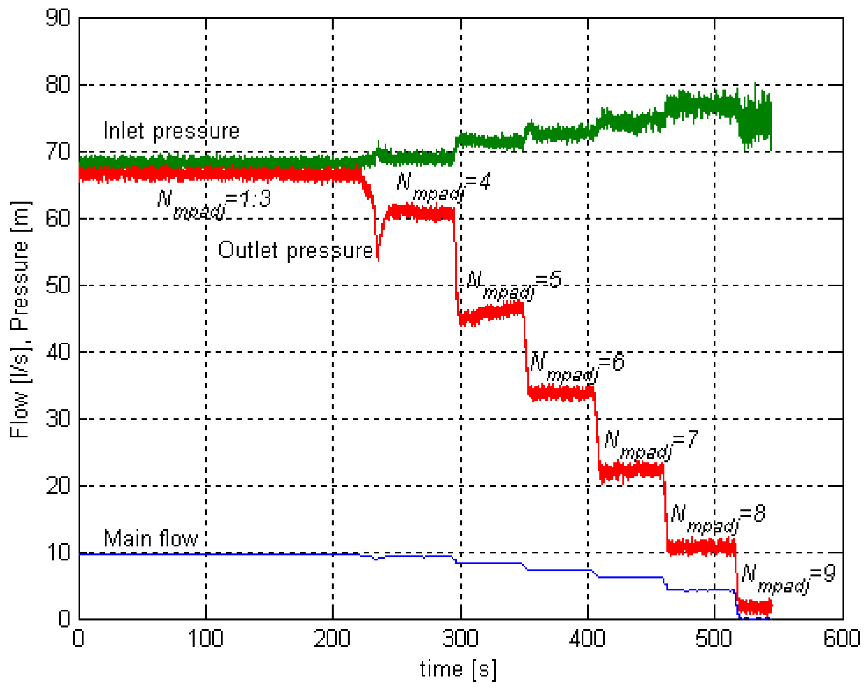


Figure 7.6. Effect of main pressure adjuster setting of the controller on the PRV outlet pressure

7.3.2.4 Sharp closure and opening of the downstream gate valve (test 4)

With the modulation adjuster set at 30% and the downstream gate valve set initially at 6 turns from complete closure, the downstream gate valve was sharply turned to almost complete closure (1 turn away from the complete closure) in less than 15 s and after 2 minutes downstream gate valve was sharply opened to the initial opening in less than 20 s. Figure 7.7 shows the results of 'test 4' where the effects of a sudden drop and subsequent rise in the main flow are displayed. By closing the downstream gate valve, the main flow decreased from 17 l/s to 1.75 l/s in 15 s, and the outlet pressure dramatically increased to its maximum value of 77.5 m in 10 s and then dropped to its nominal value of 24.6 m. However, sharp opening of the downstream gate valve, hence rapid flow increase, did not have such significant transient effect on the outlet pressure. The dynamic behaviour for each time interval in Figure 7.7 is explained below.

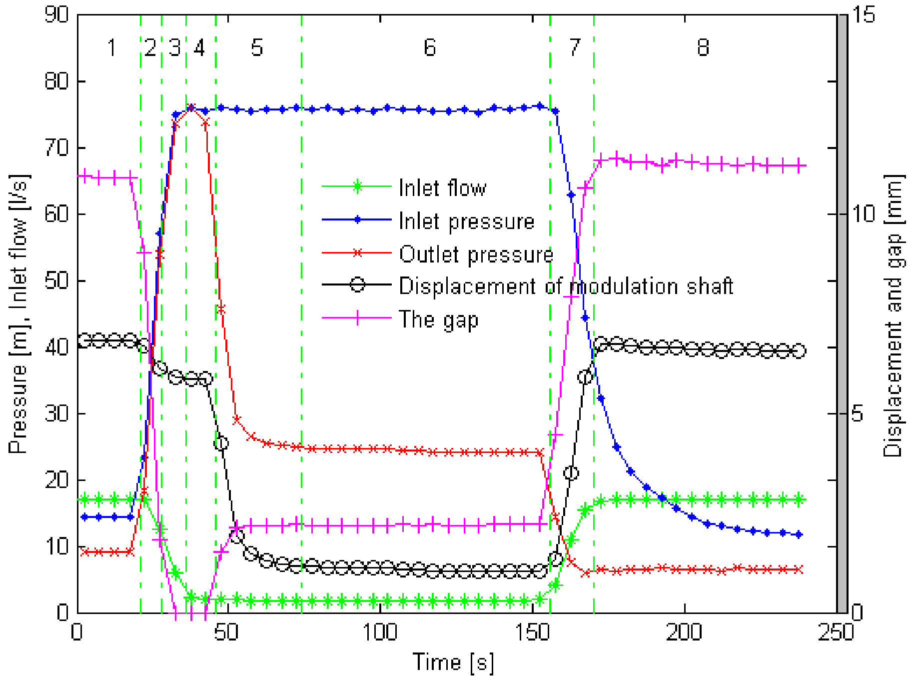


Figure 7.7. Dynamic effect of quick drop and rise in the main flow

In interval (1) the main flow is high which causes the inlet pressure to be low due to the pump characteristic. The desired outlet pressure cannot be maintained and the PRV is almost fully opened.

In interval (2) the main flow is decreasing and this has the following effects: (a) The inlet pressure is increasing due to the pump characteristic (b) The PRV is still fully opened and the outlet pressure is almost equal to the inlet pressure (increasing) (c) The modulating shaft moves to the left because of decreasing dynamic pressure (d) The pilot shaft is moving to the right because of the increasing outlet pressure.

In interval (3) the main flow is still decreasing but: (a) The jet outlet of the modulating shaft is engaged with the seat of the pilot shaft thus the modulating shaft stops (b) The PRV is still fully opened and the outlet pressure is almost equal to the inlet pressure (increasing).

In interval (4) the main flow is now constant and this has the following consequences: (a) the inlet pressure is constant (b) the gap between the jet outlet and the seat of the pilot shaft is zero and the pressure in the control chamber and T-junction rapidly increases. This results in flow, q_3, going into the control space of the PRV and forcing the main element of the PRV to move down, i.e. the PRV is closing (c) The outlet pressure is decreasing and so is the pressure acting on the pilot shaft diaphragm (d) The pilot shaft moves very slowly to the left and so does the modulating shaft; both of them are still engaged.

In interval (5) the main flow is constant and the PRV and its controller undertakes normal operation: (a) The main element of the PRV continues to move down (flow q_3 keeps going into the control space of the PRV) (b) The outlet pressure is decreasing (c) The pilot shaft moves to the left and so does the modulating shaft driven by the spring; the gap between the jet outlet and the seat of the pilot shaft is close to zero (d) At the end of this period the steady-state is achieved: (i) the modulating shaft stops at the position where forces from the dynamic pressure and spring 1 are balanced, (ii) the pilot shaft stops at the position where forces from outlet pressure and spring 2 are balanced, (iii) the gap between the jet outlet and the seat of the pilot shaft is such that the pressure at T-junction equals the pressure in the PRV control space: flow q_3 is zero and the PRV stops closing.

In interval (6) the main flow is constant and the PRV and its controller are in steady state.

In interval (7) the main flow is increasing rapidly due to opening of the downstream gate valve and this causes the following: (a) The modulating shaft moves to the right due to increase in the flow and resulting increase in the dynamic pressure; it stops when the dynamic pressure is balanced by the force of the spring 1 (b) The inlet and outlet pressures are decreasing rapidly due to the pump characteristic and so is the pressure acting on the pilot shaft diaphragm, hence the pilot shaft moves to the left (c) The gap between the jet outlet and the seat of the pilot shaft becomes large and has small resistance, therefore the pressure in the control chamber and T-junction rapidly decreases. This results in flow q_3 going out of the control space of the PRV and forces the main element of the PRV to move up, i.e. the PRV is opening.

In interval (8) the main flow becomes constant and has a high value; the following occurs: (a) The dynamic pressure is constant and the modulating shaft stops balanced by the force from the spring 1 (b) The PRV is still opening trying to maintain the outlet pressure and subsequently the inlet pressure is decreasing due to distribution of the pressure between the upstream gate valve and the PRV (c) Finally the PRV and its controller reach steady state and the PRV is almost fully opened.

In the case of rapid decrease in the flow combined with rapid increase in the inlet pressure, the PRV is fully opened, and the outlet is the same as the inlet for a few seconds then the controller closes the valve to the desired outlet pressure. Such a situation should not arise during the normal operation of a WDS. In all other cases the flow modulates the outlet pressure smoothly to the desired values.

7.3.3 Experiments to identify component parameters

An approach of deriving phenomenological model of the system was adopted as described in the section "Mathematical Model Description". Due to the lack of technical specification provided by the manufacturer, the physical characteristics for some components (e.g. modulation valve, fixed orifice, etc.) were measured as described below and calibrated separately based on the best fit.

7.3.3.1 Measuring discharge capacitance of the modulation adjuster (test a)

A water tank was placed at the height of 1.5 m. The modulation adjuster valve was detached from the controller and installed on an elastic pipe. One end of the pipe was connected to the tank bottom, another pipe end was positioned at different heights (40 cm, 60 cm, 80 cm, 100 cm and 120 cm) with respect to the water level in the tank in order to measure flow through the pipe for different pressure differences. The choice of pressure differences was consistent with the pressures in the Pitot and jet chambers of the controller observed during normal operating conditions. Water was discharged from the tank through the pipe and modulation adjuster valve into a measuring cylinder and the flow was calculated from the volume over a given period of time (approximately 30 s). Such an approach was adopted because the flow was too small to be measured with the available low-flow flowmeter. The measurements were carried out for all possible combinations of modulation valve openings (from 10% to 80% in steps of 10%) and of pressure differences (from 0.4 m to 1.2 m in steps of 0.2 m).

7.3.3.2 Measuring discharge capacitance of the of pilot valve (test b)

Since the pilot valve could not be detached from the controller, its discharge capacitance was evaluated during normal operation of the controller. Low-range flow meter was installed between T-junction (*t1*) and control chamber (Position 1) to measure flow q_2, for different gaps x_r between the jet outlet and jet seat. Note that x_r cannot be directly manipulated during the valve operation. To force the changes in x_r the downstream gate valve opening was changed causing the main flow to vary from 1.75 to 17 l/s. This was carried out for different settings of the modulation valve, i.e. for 30%, 40%, 50% and for 60% of maximum opening.

7.4 Mathematical Model Description

To provide a good understanding of the static and dynamic behaviour of the PRV and the AQUAI-MOD® hydraulic controller, a full phenomenological model has been developed. In this study, the developed model does not include the effect of pressure waves (water hammer) in the pipes of the system. The phenomenological model developed by (Prescott and Ulanicki 2003) has been used to model the behaviour of a standard PRV, while the mathematical model of the controller has been developed here.

Three moving parts are considered; the first is the main element of the PRV with the other two being the modulating and pilot shafts of the controller as depicted in Figure 7.1. The displacement of each moving part is described by a second order differential equation, equation (7.1) for the main element of the PRV, and equations (7.2) and (7.3) for the modulating shaft and the pilot shaft of the controller, respectively.

$$m_m \ddot{x}_m = \rho g \left[h_{in} a_1 + h_{out} \left(a_2 - a_1 \right) - h_{vc} a_2 \right] - m_m g - f_m \dot{x}_m + \rho \frac{q_m^2}{a_1} \tag{7.1}$$

$$m_{sh1} \ddot{x}_{sh1} = \rho g \left(h_{cpt} - h_{cj} \right) A_1 - k_{sp1} x_{sh1} - f_{sh1} \dot{x}_{sh1} + \rho \frac{q_2^2}{A_j} \tag{7.2}$$

$$m_{sh2} \ddot{x}_{sh2} = \rho g h_{cj} A_2 - k_{sp2} x_{sh2} - f_{sh2} \dot{x}_{sh2} - \rho \frac{q_2^2}{A_j} \tag{7.3}$$

The scripts, *m, x, f* and *h* denote the mass in [kg], the displacement in [m], the friction coefficient opposing the movement of the element in [kg/s] and the head in [m]. *k* is the stiffness coefficient of the spring in [kg/s^2]. q_m, q_1 and q_2 are the main flow through the PRV, the flow from the PRV inlet to T-junction (*t1*) and the flow from the control space of the PRV to T-junction (*t1*) in [m^3/s]. a_1 and a_2 are the bottom and the top areas of the main element of the PRV in [m^2]. A_1, A_2 and A_j are the internal cross sectional areas of the large and small cylinders of the controller and the discharge area of the jet in [m^2]. ρ and g are the density of water in [kg/m^3] and the gravitational acceleration in [m/s^2]. The subscripts, *m*, *sh1* and *sh2* refer the moving element of the PRV, the modulating and pilot shafts of the AQUAI-MOD® controller. *in* and *out* refer the inlet and outlet of the PRV, and *vc* refers to the control space of the PRV. *cpt*, *cc* and *cj* refer the Pitot chamber, the control chamber and the jet chamber of the controller. *sp1* and *sp2* denote the springs on the modulating and pilot shafts of the controller.

The force terms in equation (7.1) are, from left to right: the inlet pressure acting on the base of the moving element, the outlet pressure acting on the region of the diaphragm around the top of the moving element, the control space pressure acting on the top of this diaphragm, the weight of the moving element, the friction acting on the moving element, and the force caused by the change of momentum of water as it hits the base of the moving element of the PRV.

The force terms in equations (7.2) and (7.3) are, from left to right: the net pressure force acting on the both sides of the rolling diaphragms, the spring force due to the deflection of the springs, the friction acting on the moving parts of the controller, and the force caused by change of momentum of water which enters the hole of the hollow modulation shaft and exit from the jet.

The PRV under consideration is a diaphragm operated so the top area of the moving element changes with the opening of the valve according to the equation below (Prescott and Ulanicki 2003)

$$a_2 = \frac{1}{3700\left(0.02732 - x_m\right)}. \tag{7.4}$$

Flows through the controller, the PRV, and the connecting pipes are described using a set of algebraic equations. The flow through the fixed orifice, the needle valve, the pilot valve, and the PRV are given by equations of the form $q=Cv(|\Delta h|)^{1/2}\,\mathrm{sign}(\Delta h)$ where q, Δh, Cv represent the flow through the element in [m^3/s], the pressure loss across the element in [m] and the discharge capacitance of the element in [$m^{2.5}$/s], respectively. sign(Δh) is the sign of Δh. The discharge capacitance of valve is expressed as a function of the valve opening. The valve discharge capacitance is usually given in the manufacturers' literature for a PRV, and for other elements can be obtained experimentally as described in section "7.3.3".

Equation (7.5) represents the flow through the PRV, where valve discharge capacitance in [$m^{2.5}$/s], denoted $Cv_{mv}(x_m)$, depends on valve opening (displacement of the PRV main element x_m), and is taken from (Prescott and Ulanicki 2003) where the same PRV were used, and is illustrated in Figure 7.8.

$$q_m = Cv_{mv}\left(x_m\right)\sqrt{h_{in} - h_{out}} \tag{7.5}$$

and where

$$Cv_{mv}\left(x_m\right) = 0.02107 - 0.0296e^{-51.1322x_m} + 0.011e^{-261x_m} \\ - 0.00325e^{-683.17x_m} + 0.0009e^{-399.5x_m}$$

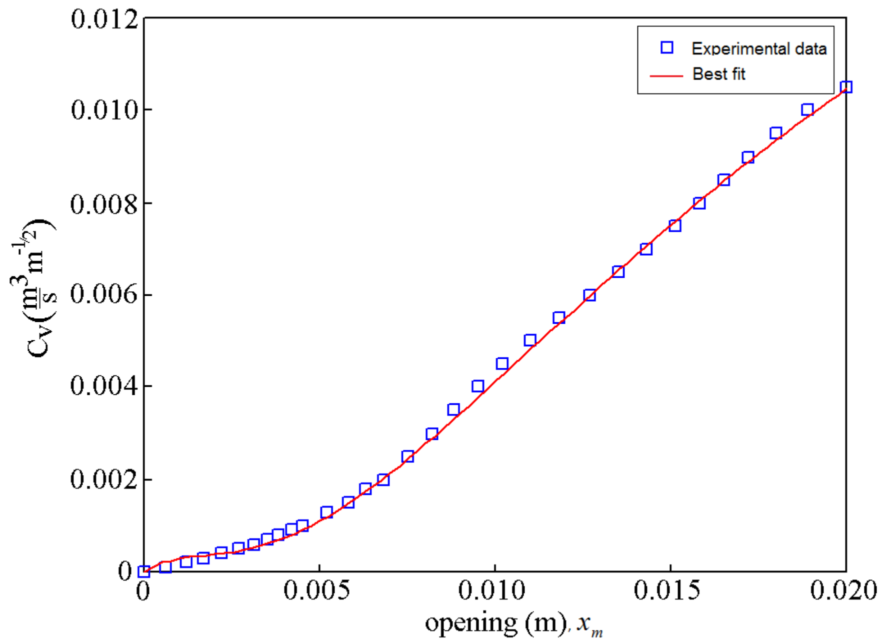


Figure 7.8. PRV capacity Cv_{mv}

The flow, denoted q_1, through the fixed orifice between the PRV inlet and the T-junction (*t1*) was measured and the discharge capacitance of the fixed orifice, denoted Cv_{fo}, is calibrated using the experimental data of 'test 1'. The flow q_1 is expressed by equation (7.6),

$$q_1 = Cv_{fo}\sqrt{h_{in} - h_{cc}} \tag{7.6}$$

where Cv_{fo} has a constant value of 8.691x10^{-6} $m^{2.5}$/s

The flow q_2, from the control chamber to the jet chamber through the discharge opening of the jet, was measured and the discharge capacitance of pilot valve in [$m^{2.5}$/s], $Cv_j(x_r)$, is calibrated against the gap x_r using the experimental data of 'tests 1, 2, and 3'. q_2 and $Cv_j(x_r)$ are described as

$$q_2 = Cv_j\left(x_r\right)\sqrt{h_{cc} - h_{cj}} \tag{7.7}$$

where

$$\begin{aligned}
&x_r = \left(x_{sh1} - x_{sh2}\right) + L_{sh1} + L_{sh2} - \left(L_{c1,2} + L_{c3}\right),\\
&L_{c3} = (79.1\ +\ 2.33\ N_{mpadj}) \times 10^{-3},\\
&Cv_j\left(x_r\right) = 0.463 \times 10^{-3}\ \left(1 - e^{-0.1073 x_r}\right)
\end{aligned}$$

where x_{sh1} and x_{sh2} are the displacements of the modulation shaft and the pilot shaft. L_{sh1}, L_{sh2}, $L_{c1,2}$, and L_{c3} are the lengths of the modulation shaft, the pilot shaft, the fixed and the variable lengths of the controller sections in [m], respectively. L_{c3} depends on the controller set-point (number of opening turns of the main pressure adjuster, N_{mpadj}), and it was measured for each experiment setting.

The flow through bi-directional needle valve q_3, has two different representations depending on the direction of flow which can be either from or to the valve control space, which is illustrated in Figure 7.9 and Figure 7.10, respectively. If flow is going out of the control space of the PRV during the valve opening, q_3 in [m^3/s] is represented by equation(7.8),

$$q_3 = Cv_{nv}\left(n\right)\sqrt{\left|h_{cc} - h_{vc}\right|} \cdot \operatorname{sign}\left(h_{cc} - h_{vc}\right) \tag{7.8}$$

where

$$Cv_{nv}(n) = (0.007753n^4 - 0.1178n^3 + 0.5357n^2 - 0.1107n - 0.01519) \times 10^{-5} \quad (7.9)$$

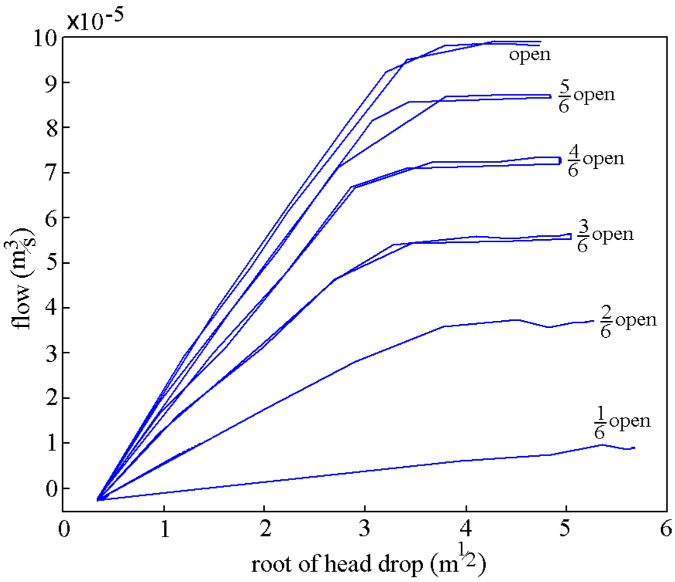


Figure 7.9. Bi-Directional needle valve capacitance (flow out of the control space) (Prescott and Ulanicki 2003)

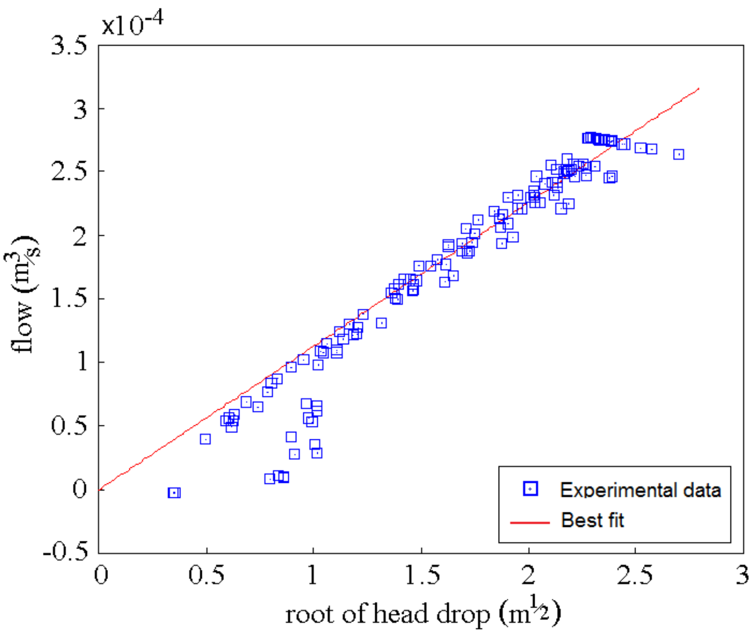


Figure 7.10. Bi-Directional needle valve capacitance (flow into the control space) (Prescott and Ulanicki 2003)

Equation (7.9) describes the relation between opening turns n of the needle valve, and the valve discharge capacitance in [$m^{2.5}$/s], Cv_{nv}, which is taken from (Prescott and

Ulanicki 2003). The bi-directional needle valve has a physical limit to deliver the flow from the control space of the PRV, which is defined as the valve saturation flow, denoted $q_{3,sat}$, (Choudhury et al. 2008) and is represented by equation (7.10), and illustrated in Figure 7.11.

$$q_{3,sat}(n) = (0.02636n^4 - 0.3574n^3 + 1.473n^2 - 0.01926n - 0.05029) \times 10^{-5} \quad (7.10)$$

In the case of the flow going into the PRV control space during PRV closure, the needle valve discharge capacitance is constant and equal to 0.11×10^{-3} $m^{2.5}/s\cdot$. The characteristics of the valve show that the PRV closes faster than it opens.

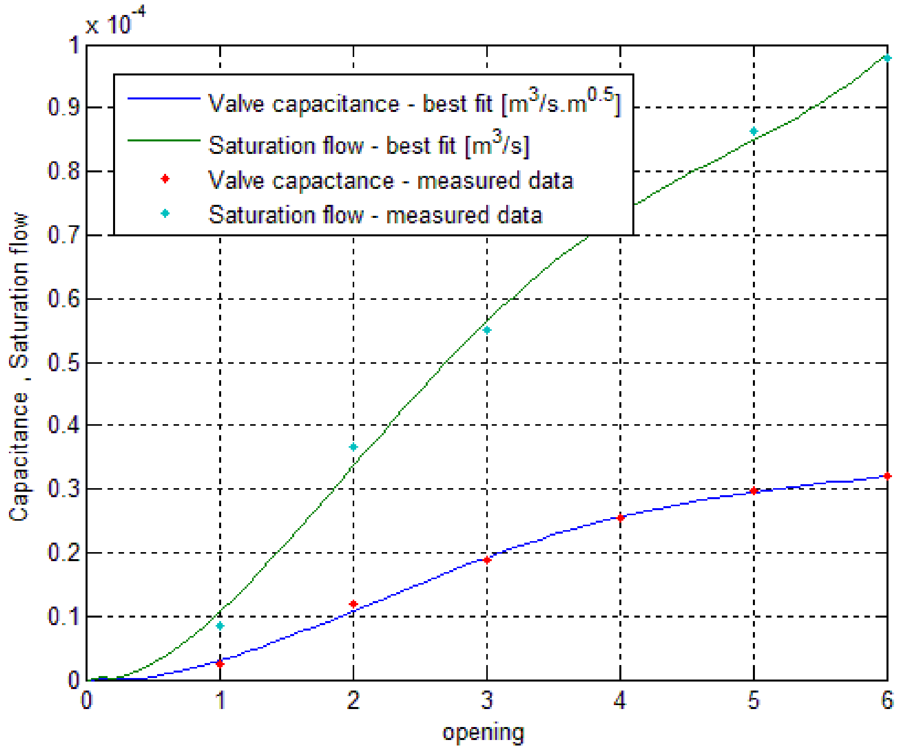


Figure 7.11. Needle valve capacitance and saturation flow

The same flow, q_3, can also be calculated from equation (7.11) as a function of displacement x_m:

$$q_3 = \frac{\dot{x}_m}{3700\left(0.02732 - x_m\right)} \tag{7.11}$$

Flow q_6, into the jet chamber through the modulation adjuster is described in [m^3/s] by equation (7.12), the modulation adjuster is a one-directional needle valve (into the jet chamber direction), and the flow is present if the pressure at T-junction *t2* (h_{t2}) is higher than pressure in the jet chamber (h_{cj}), otherwise the valve is closed. Discharge capacitance of the modulation adjuster, $Cv_{ma}(n)$ was calibrated using the results of 'test a' for different number of opening, *n*, and is valid for $0 \le n \le 8$.

$$q_6 = Cv_{ma}\left(n\right)\sqrt{\left|h_{t2} - h_{cj}\right|} \cdot \mathrm{sign}\left(h_{t2} - h_{cj}\right) \tag{7.12}$$

where

$$\begin{aligned} Cv_{ma}\left(n\right) = 10^{-4}[&2.371 - 2.4240\cos(0.5015n) - 1.814\sin(0.5015n) \\ &- 0.2775\cos(1.0030n) + 1.230\sin(1.0030n) \\ &+ 0.3311\cos(1.5045n) - 0.1315\sin(1.5045n)] \end{aligned}$$

The relation between the pressure drop and flow q_4 in [m^3/s] through the pipe between the Pitot tube and T-junction *t2*, is described by Darcy–Weisbach formula given by equation (7.13)

$$h_{out,t} - h_{cpt} = f_4 \frac{L_4}{D_4} \frac{1}{2g} \left(\frac{q_4}{A_4}\right)^2 \tag{7.13}$$

where the total pressure, denoted $h_{out,t}$, is equal the PRV outlet pressure plus the dynamic pressure in the Pitot tube. L_4, D_4, A_4, and f_4 are the length, the diameter in [m], the internal cross sectional area in [m^2] and the friction coefficient of the connecting pipe.

The equation can be re-arranged to obtain q_4

$$q_4 = A_4 \sqrt{2g \frac{D_4}{f_4 L_4}} \sqrt{h_{out,t} - h_{cpt}} \tag{7.14}$$

where

$$h_{out,t} = h_{out} + \frac{1}{2g}\left[\left(\frac{q_m}{A_{mv,out}}\right)^2 - \left(\frac{q_4}{A_{Pitot}}\right)^2\right]$$

where $A_{mv,out}$ and A_{Pitot} are the cross sectional areas of the PRV outlet and Pitot tube, respectively.

Finally, the flow from/to the Pitot chamber can be calculated from the change in the volume of the Pitot chamber, as shown in equation (7.15).

$$q_5 = \dot{x}_{sh1} A_1 \tag{7.15}$$

The mass balance equations (7.16) and (7.17) for junctions *t1* and *t2* respectively complete the algebraic part of the model

$$q_1 + q_3 = q_2 \tag{7.16}$$

$$q_5 + q_6 = q_4 \tag{7.17}$$

The pump characteristic has been estimated from the test rig measurements, and the delivered pressure, h_{in}, can be expressed as a cubic function of the main flow

$$h_{in} = -0.026\times10^9 q_m^3 + 0.3562\times10^6 q_m^2 - 1.8605\times10^3 q_m + 77.947 \tag{7.18}$$

where q_m is in [m^3/s] and h_{in} in [m].

The described model can be simplified by ignoring the inertia and friction terms (the second and first derivatives of *x*) in equations (7.1), (7.2) and (7.3). The model can be further simplified by ignoring the pressure drops in the short connecting pipes and assuming that $h_{t1}=h_{cc}$, $h_{t2}=h_{cpt}$, and $h_{cj}=h_{out}$.. In this chapter during the simulations, the friction terms in the model have been ignored.

7.4.1 Structure of the model

In order to better understand the mathematical structure of the model the formal state space notation is introduced. Define the state vector **x**, the vector of algebraic variables **y** and the vector of parameters **μ** as follows:

$$\mathbf{x}=\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{bmatrix}=\begin{bmatrix} x_m \\ \dot{x}_m \\ x_{sh1} \\ \dot{x}_{sh1} \\ x_{sh2} \\ \dot{x}_{sh2} \end{bmatrix},\qquad \mathbf{y}=\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \\ y_6 \\ y_7 \\ y_8 \\ y_9 \\ y_{10} \\ y_{11} \\ y_{12} \\ y_{13} \end{bmatrix}=\begin{bmatrix} h_{out} \\ h_{vc} \\ h_{cpt} \\ h_{cj} \\ q_1 \\ q_2 \\ q_3 \\ q_4 \\ q_5 \\ q_6 \\ x_r \\ Cv_j \\ h_{out,t} \end{bmatrix},\qquad \boldsymbol{\mu}=\begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \\ \mu_6 \\ \mu_7 \\ \mu_8 \\ \mu_9 \\ \mu_{10} \\ \mu_{11} \\ \mu_{12} \\ \mu_{13} \\ \mu_{14} \\ \mu_{15} \\ \mu_{16} \\ \mu_{17} \\ \mu_{18} \\ \mu_{19} \\ \mu_{20} \\ \mu_{21} \\ \mu_{22} \\ \mu_{23} \end{bmatrix}=\begin{bmatrix} \rho \\ g \\ a_1 \\ a_2 \\ m_m \\ m_{sh1} \\ A_1 \\ k_{sp1} \\ A_j \\ m_{sh2} \\ A_2 \\ k_{sp2} \\ q_m \\ h_{in} \\ Cv_{mv} \\ Cv_{fo} \\ L_{C3} \\ Cv_{nv} \\ q_{3,sat} \\ Cv_{ma} \\ k_4 \\ A_{mv,out} \\ A_{Pitot} \end{bmatrix} \tag{7.19}$$

The additional relationships between state variables can be derived from their definitions

$$\dot{x}_1 = x_2 \tag{7.20}$$

$$\dot{x}_3 = x_4 \tag{7.21}$$

$$\dot{x}_5 = x_6 \tag{7.22}$$

The general structure of the model can be represented by a vector differential algebraic equation:

$$\begin{cases} \dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{y}(t), \boldsymbol{\mu}) \\ \mathbf{g}(\mathbf{x}(t), \mathbf{y}(t), \boldsymbol{\mu}) = \mathbf{0} \end{cases} \tag{7.23}$$

There are six state equations; the first equation is defined by equation (7.20), the second by equation (7.1), the third by equation (7.21), the fourth by equation (7.2), the fifth by equation (7.22) and finally the sixth by equation (7.3). The algebraic part **g(x,y,μ)** is defined by equations (7.4) to (7.18) excluding equation(7.13).

7.4.2 Singularity in the model

Initially the model was implemented in Matlab but despite trying many different solvers the simulations failed to converge and consequently it was decided to use the Mathematica package. In order to accomplish a better understanding of the PRV behaviour and to identify numerical problems encountered in the simulation a simplified problem has been solved analytically (in steady state conditions and without the outlet pressure modulation).

Equation (7.1) in steady state condition becomes

$$\rho g\left[h_{in}a_1 + h_{out}\left(a_2 - a_1\right) - h_{vc}a_2\right] - m_m g + \rho\frac{q_m^2}{a_1} = 0 \tag{7.24}$$

Moreover $h_{cc} = h_{vc}$, $q_3 = 0$ and $q_5 = 0$, hence $q_1 = q_2$ and $q_4 = q_6$. In the steady state x_r is constant and subsequently $Cv_j(x_r)$ is constant too. Then from equations (7.5) and (7.6),

$$h_{vc} = \beta_1 h_{in} + \beta_2 h_{out} \tag{7.25}$$

where

$$\beta_1 = \frac{Cv_{fo}^2}{Cv_{fo}^2 + Cv_j^2}, \text{ and } \beta_2 = \frac{Cv_j^2}{Cv_{fo}^2 + Cv_j^2}$$

which confirms that the pressure in the control space of the PRV is a convex combination of the inlet and outlet pressures.

Substituting h_{vc} from (7.24) and (7.25) allows to evaluate h_{out}

$$h_{out} = h_{in} - \frac{\left(\frac{m_m}{a_1 \rho}\right) - \left(\frac{q_m^2}{a_1^2 g}\right)}{\left(1 - \frac{a_2}{a_1}\beta_1\right)} \tag{7.26}$$

The value of β_1 depends on the discharge capacitance and it can happen that the term $\left(1 - \frac{a_2}{a_1}\beta_1\right)$ is close to zero causing a singularity in equation (7.26) as depicted by the plot in Figure 7.12. The singularity happens for $\beta_{1,critical} = \frac{a_1}{a_2}$. The branch of the plot for $\beta_1 < \beta_{1,critical}$ represents the physical situation when the outlet pressure is smaller than the inlet pressure, whilst the branch of the plot for $\beta_1 > \beta_{1,critical}$ is just a mathematical construct. The value of h_{out} tends to $-\infty$ just before $\beta_{1,critical}$ and rises to $+\infty$ just after $\beta_{1,critical}$. If a numerical solver starts with an initial guess corresponding to $\beta_1 > \beta_{1,critical}$ it may fail to converge to a physical solution, which probably was the reason for the failure of the Matlab simulations.

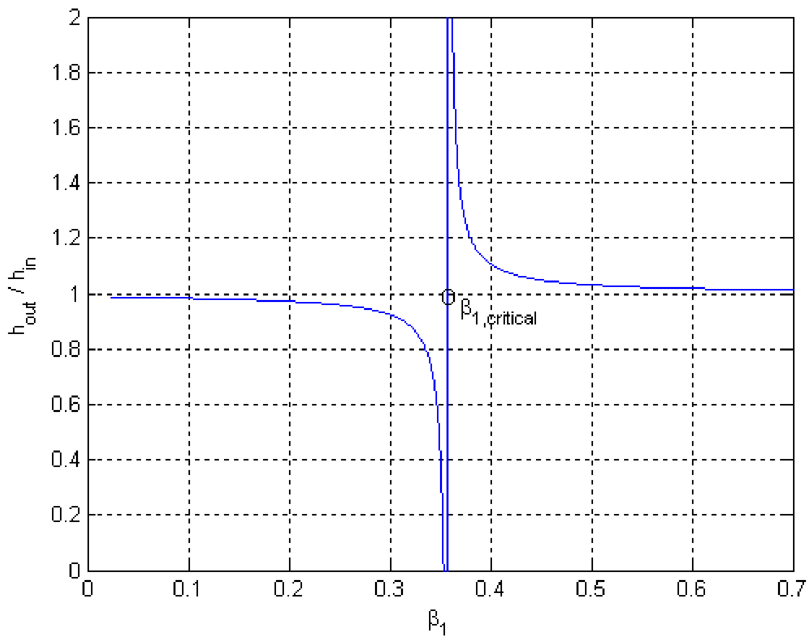


Figure 7.12. The solution of equation (7.26) for a given inlet pressure and flow.

7.5 Results and Discussions

The results of the mathematical model compared to the experimental data in steady state operation and dynamic conditions are presented in the sections below in order to validate the developed mathematical model. In addition, it aims to show the behaviour of the PRV subject to deferent setting of the controller, as well to demonstrate the characteristics of the system under different operating conditions to evaluate its performance especially its dynamic behaviours.

7.5.1 Steady state results

A number of steady state characteristics were measured as an initial assessment of the functionality and robustness of the AQUAI-MOD® hydraulic controller. The corresponding the mathematical model has been solved using the Mathematica® software package and subsequently the numerical results have been compared with the measurements to validate the developed mathematical model. In particular, effects of the flow modulation adjuster and the main pressure adjuster have been investigated in steady state to evaluate the performance of the controller.

7.5.1.1 Modulation adjuster effect

Figure 7.13 depicts a family of the modulation curves for different settings of the modulation adjuster and for fixed 6.5 opening turns of the main pressure adjuster ('test 1 and 2'). The solid lines represent results from the model and the coloured patches represent noisy measurements. It can be observed that when the main flow increases the outlet pressure of the PRV increases confirming the flow modulation effect. The pressure drop at high flows is due to the test rig arrangement, i.e. the PRV inlet pressure decreases due to the pump characteristics. The modulation effect is more prominent for almost closed modulation adjuster. The effect of the modulation almost disappears for the almost fully opened adjuster.

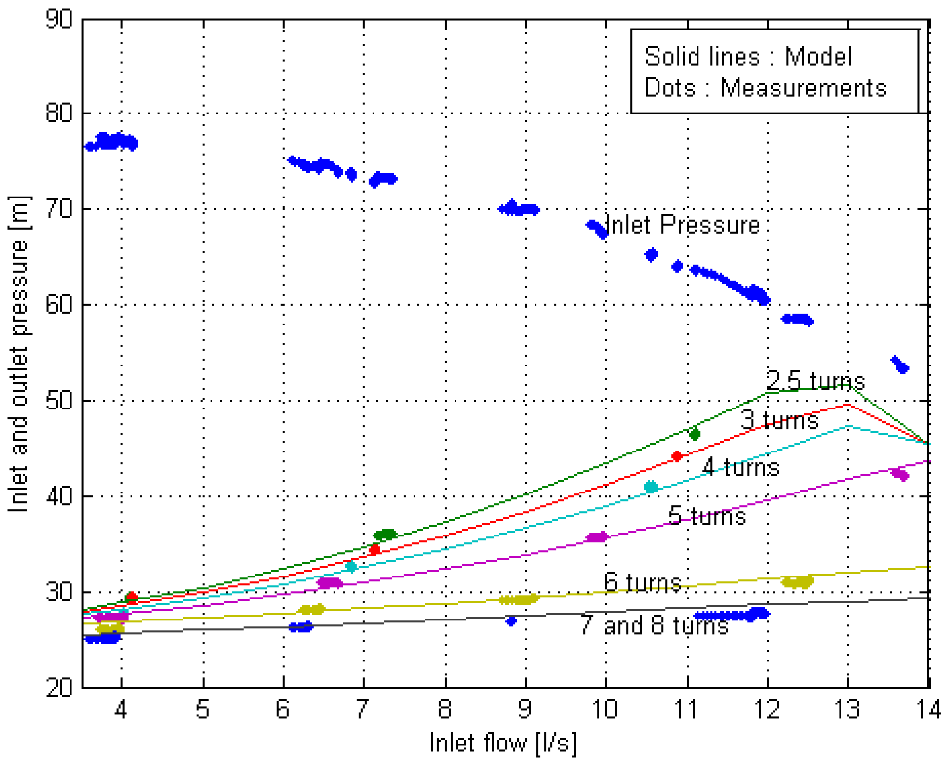


Figure 7.13. Modulation curve of the AQUAI-MOD® controller at different setting of modulation adjuster and 6.5 opening turns of main pressure adjuster

7.5.1.2 Main pressure adjuster effect

Figure 7.14 shows a family of the modulation curves for different number of opening turns of the main pressure adjuster ('test 4') again the solid lines represent results from the model and the coloured patches represent noisy measurements. It can be observed that settings in range 0-3 turns have no effect, and the outlet pressure stays almost constant, which means that the PRV is fully opened. More turns corresponds to a lower 'minimum pressure set-point', for each opening turn the modulation curve shifts down by 12 m in average as it can be observed.

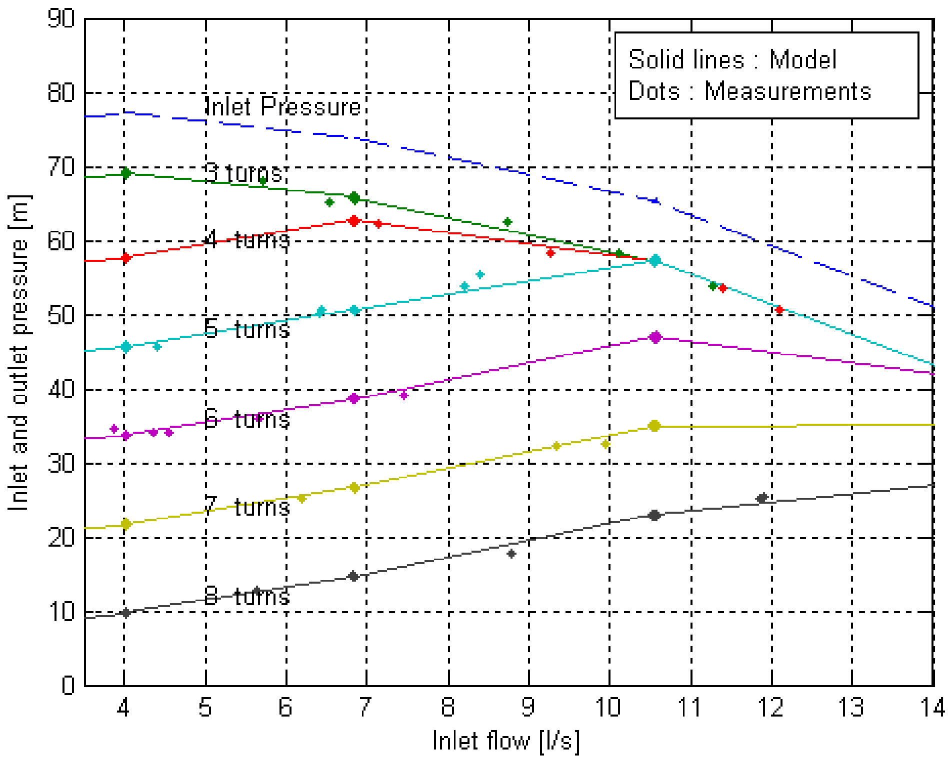


Figure 7.14. Modulation curve of the AQUAI-MOD® controller at different setting of main pressure adjuster and 4 opening turns of modulation adjuster

7.5.2 Typical operating condition in steady state

The steady state model has been validated by comparing the results of the model and the experimental data during different regimes of the valve operation in a typical operating condition of both the inlet flow and pressure. The experimental main flow and the inlet pressure have been used as given inputs to the mathematical model. In all cases the steady state model results show a good agreement with the experimental data in trends and magnitudes. Figure 7.15 shows the experimental inlet flow, the inlet pressure and the outlet pressure as well the results of the steady state mathematical model. In this case, the minimum pressure was set by the main pressure adjuster (6.5 opening turns) to 26 m corresponding to the minimum flow of 1.85 l/s, and the maximum pressure was set by the main modulation adjuster (4 opening turns) to 41.5 m corresponding to the flow of 10.6 l/s. Minimum and maximum flow have been chosen to be in the normal operating range for the PRV. A very good agreement between the experimental outlet pressure values and the simulated outlet pressure of the model is observed with relative root mean squared error of 0.090.

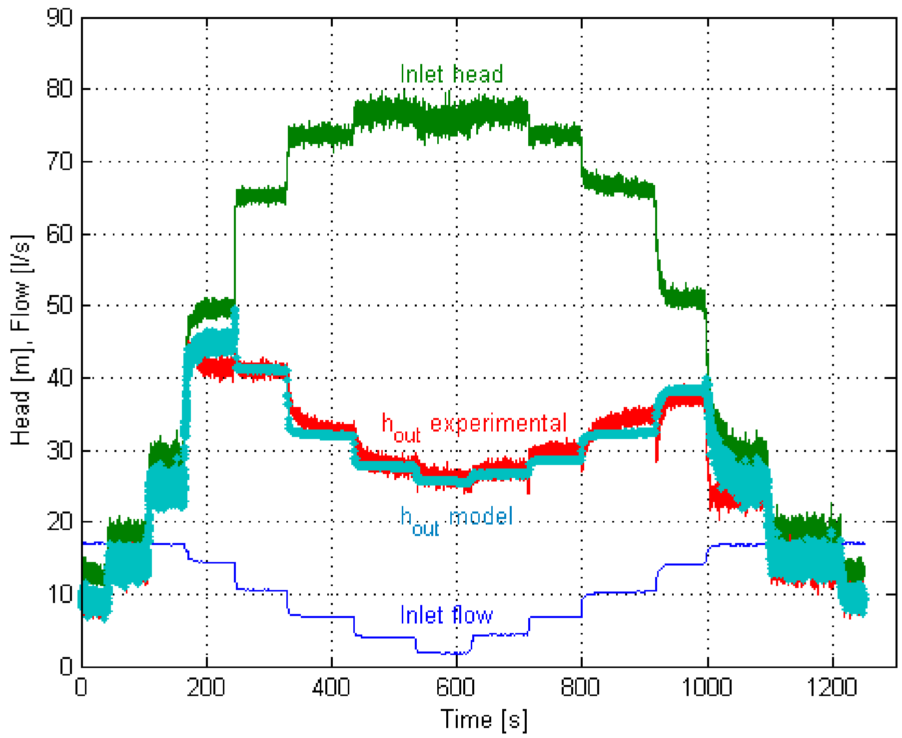


Figure 7.15. Steady state model results compared with experimental data for step decreasing followed by step increasing of inlet flow

7.6 Dynamic Results

The mathematical model including the dynamic aspects has been solved using Mathematica software package to evaluate the behaviour of the system for varying main valve flow. The results of the mathematical model have been compared with the experimental data obtained from the test rig to validate the model in dynamic conditions. The comparison showed a good agreement in the values and trends, as shown in Figure 7.16, for a typical operating condition in terms of flow and inlet pressure, with the modulation adjuster set up to 3 turns and the main pressure adjuster to 6.5 turns. These settings correspond to the minimum pressure of 26 m (minimum flow of 1.85 l/s), and the maximum pressure of 45 m (flow of 11 l/s). The relative root mean squared error between the results from the model and the experimental data has a value of 0.100.

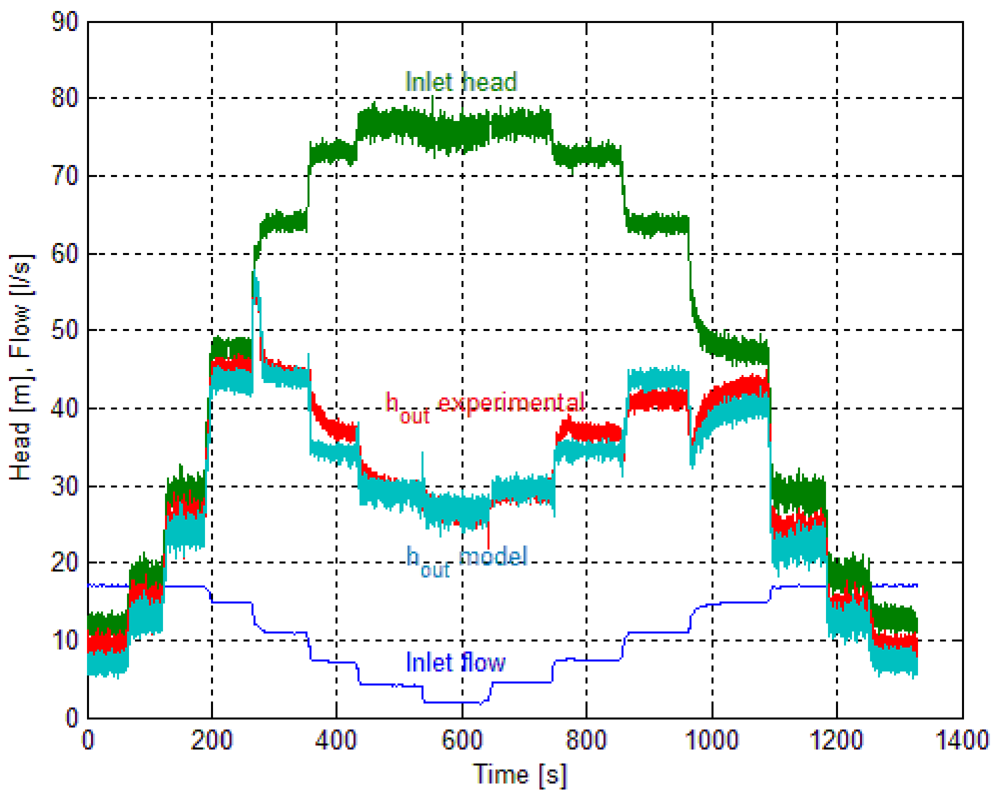


Figure 7.16. Results of dynamic model compared with experimental data for stepping the inlet flow down and up.

Figure 7.17 shows the results of the dynamic model compared with experimental data for a sharp closure of the downstream gate valve with the modulation adjuster set up to 3 turns and the main pressure adjuster to 6.5 turns as described in 'test 4'. The mathematical model does not consider water hammer in the pipes of the system. Note that the closure of the downstream gate valve is not sufficiently fast to show any water hammer effects. Both experimental data and the numerical results showed a good agreement in both trend and magnitude, and have an error of 0.080 in terms of relative root mean squared error.

As shown in the figure there is a difference between the measured and simulated outlet pressures for t = 47 s. The measured pressure decreases at a slower rate and this is probably due to the simplifying assumptions ignoring friction forces.

It was observed from both experiments and modelling studies that the dominant dynamic behaviour of the PRV equipped with the AQUAI-MOD® controller is decided by the movement of the PRV main element and is the same as a standard PRV with a pilot valve.

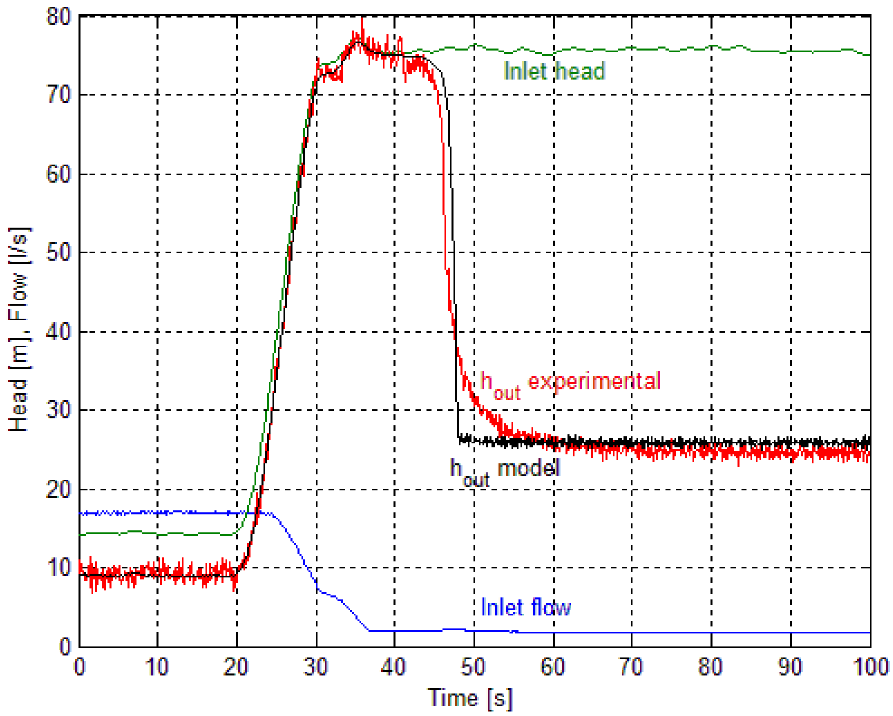


Figure 7.17. Results of dynamic model compared with experimental data of sharp closure, with 3 opening turns of modulation adjuster and 6.5 of main pressure adjuster

7.7 Summary

The AQUAI-MOD® hydraulic controller is a device to control and modulate the outlet pressure of a PRV according to the valve flow. The modulation curve is defined by the set-points for the minimum and the maximum outlet pressure corresponding to the minimum and the maximum flow, respectively. The controller was experimentally tested via carefully designed experiments to assess its performance and functionality in different conditions and operating ranges. The controller in all cases showed a good performance by modulating the outlet pressure between the minimum and maximum set-points as expected. The dynamic behaviour of the valve was also tested and presented, followed by a detailed explanation. The controller was worked as expected in all tested conditions and it was found that the dominant dynamic behaviour of the PRV equipped with the AQUAI-MOD® controller is the same as a standard PRV with a pilot valve. It is considered that such hydraulic flow-modulated devices could be used to reduce the leakage while satisfying pressure requirements.

The mathematical model of the controller has been developed and solved with the Mathematica® software package, in both steady state and dynamic conditions. The results of the model have been compared with the experimental data and showed a good agreement in the magnitude and trends. The developed models can be used to compute the required adjustment for the minimum and maximum pressure set-points before installing the controller in the field, or to simulate the behaviour of a PRV and the AQUAI-MOD® hydraulic controller in typical network applications.

It is considered that the experiment design and modelling approach described in this chapter can be helpful for other authors developing mathematical models of similar systems. Such models can be used at the design stage to size the components of a hydraulic controller and to improve its characteristics. They can also be integrated with water network simulators to study the behaviour of WDSs governed by hydraulic flow-modulation controllers.

Chapter 8

8 Combined Pressure, Leakage and Energy Management in Water Distribution Systems

In this chapter, integration algorithm between pump scheduling for energy management and DMA pressure control for leakage reduction is developed. Traditionally these tasks are considered separately but if the PRV inlet pressure is higher than required, in the cases when this is possible (i.e. when there is not an intermediate distribution reservoir at the upstream side) it can be reduced by adjusting pumping schedules in the upstream part of the network. Many modern pumps are equipped with variable speed drives, and manipulating speed is a very efficient method of reducing energy use – (the power consumption changes with the cube of the speed). The proposed approach is based on NLP and novel local search ideas supported by heuristics derived from numerous industrial case studies. The module calculates time schedules for treatment works, pumps, valves and reservoirs.

8.1 Introduction

Optimal pressure control, pump scheduling, and operating policies of the multi-source, multi-reservoir system have been investigated by researchers over many years and different approaches have been developed. The scheduling problem is nonlinear, dynamic and mixed-integer and is numerically hard to solve. However, it lends itself well to different simplifying assumptions to calculate near-optimal solutions. The available solutions are applicable to grid systems, but significant research is required to link these to pressure control aspects (i.e., valve scheduling and leakage reduction) which can be selectively applied, especially in those parts of the system with direct pumping.

The main objective of energy and pressure managements in water supply systems is to minimise the operating cost in terms of electricity charges for pumping, treatment costs and charges for imported water while satisfying operating constraints. The relevant operating constraints typically include the following:

- Maximum and minimum water levels in reservoirs

- Maximum and minimum allowable pressures in the mains or distribution pipes
- Patterns of demand which must be satisfied
- Power supply limitations
- Constraints on the combinations of pumps, which can be run together
- Maximum and minimum time of the pump operation, ON/OFF time
- Maximum and minimum speeds for the variable speed pumps.

The proposed method for combined energy and pressure management, based on formulating and solving an optimisation problem, is an extension of the pump scheduling algorithms described in Bounds et al. (2006). The method involves utilisation of a hydraulic model of the network with pressure dependent leakage with the PRV set-points included in a set of decision variables. The cost function represents the total cost of water treatment and pumping energy. An excessive pumping contributes to a high total cost in two ways. Firstly, it leads to high energy usage. Secondly, it induces high pressure, hence increased leakage, which means that more water needs to be pumped and taken from sources. Therefore, the optimizer, by minimising the total cost, attempts to optimize the energy usage, reduce its cost and minimise the leakage. In the optimisation problem considered some of the decision variables are continuous (e.g. water production, pump speed, and valve setting) and some are integer (e.g. number of pumps switched ON). Problems containing both continuous and integer variables are called mixed-integer problems and are hard to solve numerically. Continuous relaxation of integer variables (e.g. allowing 2.43 pumps ON) enables network scheduling to be treated initially as a continuous optimisation problem solved by a non-linear programming algorithm. Subsequently, the continuous solution can be transformed into an integer solution by manual or automatic post-processing, or by further optimisation. For example, the result "2.5 pumps ON" can be realised by a combination of 2 and 3 pumps switched over the time step. Section "8.3" describes continuous optimisation problem solved by a non-linear programming algorithm, while in section "8.4" a schedule discretisation algorithm that allows the user to interact with the discretisation process is described.

Remark 1. *An experienced network operator is able to manually transform continuous pump schedules into equivalent discrete schedules (Ulanicki et al. 2007).*

Optimisation methods described in this work are model-based and, as such, require hydraulic model of the network to be optimised. Such hydraulic model is usually developed in a modelling environment such as Epanet, Finesse, etc. and consists of three main components: boundary conditions (sources and exports), a hydraulic nonlinear network made up of pipes, pumps, valves, and reservoir dynamics. In order to reduce the size of the optimisation problem the full hydraulic model has been simplified using model reduction algorithm (Shamir and Salomons 2008; Ulanicki et al. 1996). In the simplified model all reservoirs and all control elements, such as pumps and valves, remain unchanged, but the number of pipes and nodes is significantly reduced. It should be noted that the connections (pipes) generated by model reduction algorithm may not represent actual physical pipes. However, parameters of these connections are computed such that the simplified and full models are equivalent mathematically. Both the NLP algorithm has been employed to compute the continuous schedule, and also schedule discretisation method, require a simulator of the hydraulic network. Simulators are part of modelling software such as Epanet or Finesse. In this work a Finesse simulator called Ginas (Rance et al. 2001) has been used to provide the initial feasible solution to the NLP solver by simulating the network, and Epanet has been utilized and linked with Matlab to discretise the continuous solution.

8.2 Optimal Network Scheduling Problem

Network scheduling calculates least-cost operational schedules for pumps, valves and treatment works for a given period of time, typically 24 hours (in the current work 7 day schedule have also been implemented). The decision variables are the operational schedules for control components, such as pumps, valves (including PRVs) and water treatment works outputs. The problem has the following three elements:

1. Objective function
2. Decision variables
3. Hydraulic model of the network
4. Constraints

The scheduling problem is succinctly expressed as: minimise (pumping cost + treatment cost), subject to the network equations and operational constraints. The three elements of the problem are discussed in the following subsections.

8.2.1 Objective function

The objective function to be minimised is the total energy cost for water treatment and pumping cost depends on the efficiency of the pumps used and the electricity power tariff over the pumping duration. The tariff is usually a function of time with cheaper and more expensive periods. For a given time step τ_c, the objective function considered over a given time horizon $[k_0, k_f]$ is given by the following equation:

$$\phi = \left(\sum_{j \in J_p} \sum_{k=k_0}^{k_f} \gamma_p^j(k) f_j\left(q^j(k), c^j(k)\right) + \sum_{j \in J_s} \sum_{k=k_0}^{k_f} \gamma_s^j(k) q_s^j(k) \right) \tau_c \tag{8.1}$$

where J_p is the set of indices for pump stations and J_s is the set of indices for treatment works. The vector $c^j(k)$ has two elements; the number of pumps being ON, denoted $u^j(k)$, and pump speed (for variable speed pumps) denoted $s^j(k)$. The function $\gamma_p^j(k)$ represents the electrical tariff. The treatment cost for each treatment works is proportional to the flow output with the unit price of $\gamma_s^j(k)$. The term $f_j\left(q^j(k), c^j(k)\right)$ represents the electrical power consumed by pump station j. The mechanical power of water is obtained by multiplying the flow $q^j(k)$ and the head increase $\Delta h^j(k)$ across the pump station. The head increase $\Delta h^j(k)$ can be expressed in terms of flow in the pump hydraulic equation, so that the cost term depends only on the pump station flow $q^j(k)$ and the control variable $c^j(k)$. Electrical power consumed by the pump can be calculated from mechanical power of water using either the pump efficiency or pump power characteristics (Ulanicki et al. 2008b). In this work pump power characteristics have been used and electrical power consumed by the pump station has been calculated by adapting the formula, taken from (Ulanicki et al. 2008b), given as follows:

$$P(q,u,s) = \begin{cases} us^3\left(E\left(\frac{q}{us}\right)^3 + F\left(\frac{q}{us}\right)^2 + G\frac{q}{us} + H \right) & \text{if} \quad u,s > 0, \\ 0 & \text{otherwise} \end{cases} \tag{8.2}$$

where E, F, G, H are power coefficient constants for a given pump. Note that, for simplicity of notation, in equation (8.2) the time-indices k and superscripts j for terms q, u, s were omitted.

8.2.2 Model of water distribution system

The fundamental requirement in an optimal scheduling problem is that all calculated variables satisfy the hydraulic model equations. The network equations are non-linear and play the role of equality constraints in the optimisation problem. The network equations used to describe reservoir dynamics, components hydraulics and mass balance at nodes and reservoirs are those described in (Ulanicki et al. 2007). Since leakage is assumed to be at connection nodes, the equation to describe mass balance at connection nodes was modified to include the leakage term:

$$\Lambda_c \mathrm{q}(k) + \mathrm{d}_c(k) + \mathrm{l}_c(k) = 0 \tag{8.3}$$

where Λ_c is node branch incidence matrix, q is vector of branch flows, d_c denotes vector of demands and l_c denotes vector of leakages calculated as

$$\mathrm{l}_c(k) = \mathrm{k}\,\mathrm{p}^{\alpha}(k) \tag{8.4}$$

with p denoting vector of node pressures, $\alpha \in \langle 0.5, 2.5 \rangle$ denoting leakage exponent and k denoting vector of leakage coefficients. Note that p^{α} denotes each element of vector p raised to the power of α.

8.2.3 Constraints

In addition to equality constraints described by the hydraulic model equations, operational constraints have been applied to keep the system-state within its feasible range. Practical requirements are translated from the linguistic statements into mathematical inequalities. The typical requirements of network scheduling are concerned with reservoir levels in order to prevent emptying or overflowing, and to maintain adequate storage for emergency purposes:

$$h_f^{\min}(k) \le h_f(k) \le h_f^{\max}(k) \quad \text{for } k \in \langle k_0, k_f \rangle \tag{8.5}$$

where $h_f(k)$ is the reservoir water level at time k. $h_f^{\min}$ and $h_f^{\max}$ are the lower and upper bounds of the reservoir constraints. Similar constraints are applied to the heads at critical connection nodes in order to maintain required pressures throughout the water network. Another important constraint is on the final water level of reservoirs, such that the final level is not smaller than the initial level; without such constraint least-cost optimisation would result in emptying of reservoirs. The control variables such as the number of pumps being "ON", pump speeds or valve settings have been also constrained by lower and upper constraints determined by the features of the control components.

8.2.3.1 Pressure constraints

Water is produced from water treatment works within Oldham region is pumped to the reservoirs that are on a higher elevations than the connected DMAs and then supplied to customers via gravity. The defined minimum reservoirs levels ensure that the pressures at the DMA inlets are always satisfied.

8.2.3.2 Constraints of the reservoirs

To quantify the cost benefit of various minimum reservoir constraints, four different lower and upper bounds in the reservoir have been proposed in Table 8.1. These limits have been applied as constraints of the reservoir level, and the defined lower reservoirs levels ensure that the pressures at the DMA inlet nodes are always satisfied, due to the high elevations of the reservoir. Only the full results of scenario S2 are presented in this thesis, while other scenarios are presented in (AbdelMeguid et al. 2009a).

Table 8.1 Scenarios of lower and upper reservoir limits*

Scenario	lower level limit	Upper level limit
S1	Min of telemetry data	95%
S2	40%	95%
S3	55%	95%
S4	70%	95%
*The limits are percents of the full reservoir level		

As shown in Figure 1.1, the reservoir initial level has been selected in the middle of the bounds. The lower bound has this specific shape to make the solver keep the final reservoir level as or higher than the initial level.

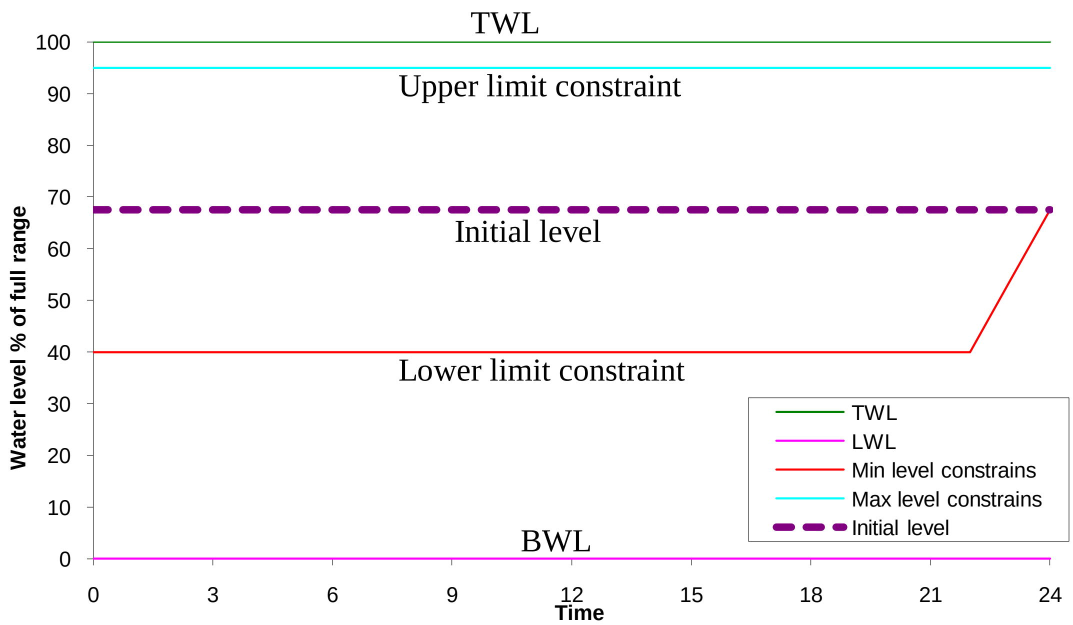


Figure 8.1. Reservoirs constraints and initial water levels

8.2.3.3 Constraints of pump stations

The constraints of the pumps include the speed for variable speed pumps and the number of pumps being "ON" and the number of switchs per day. Formally, a pump switching is defined as changing the pump status, ON/OFF or OFF/ON. The wear and tear of pumps is mainly caused by frequent switching, therefore, minimising the number of switching results in minimisation of maintenance costs, also protect the network from frequent pressure fluctuations. In this study, the minimum time before changing a pump status is 30 minutes, and for variable speed pumps the lower and upper speed limits have been taken as 50% and 100% of the rated speed, respectively.

8.2.3.4 Constraints of water treatment works

Table 8.7 shows the constraints on water production in water treatment works which includes production and ramp-up rate.

8.3 Using GAMS to Solve Network Continuous Scheduling Problems

In this study, the network scheduling problem has been solved by using the general algebraic modelling system language called GAMS and the non-linear programming solver CONOPT3 (Drud 1994, 2008). Using a high-level modelling language such as

GAMS enables a clear separation between modelling a problem and execution of optimization by CONOPT. These software components have been integrated into Finesse that includes a complementary network simulator as well as common data editing, analysis and storage services. As a result, the network scheduler has become another practical analysis tool to help the engineer make more informed decisions and make tangible savings. More details about GAMS code and CONOPT are presented in Appendix A.

8.3.1 The network scheduling problem

The conceptual formulation of the optimal control scheduling problem is illustrated in Figure 8.2 and written in plain English as follows:

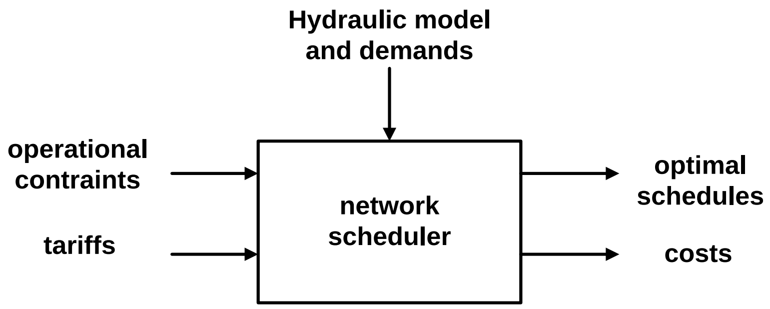


Figure 8.2 System model of a network scheduler

Minimise (pumping cost + treatment cost) subject to the network equations and the operational constraints where the decision variables are operational schedules for control elements such as pump schedules, valve schedules, and water production schedules at treatment works.

This conceptual formulation has been converted into a set of equations. Network equations are given by energy conservation, mass balance, and the element laws, as introduced in Chapter 3.

8.4 Discretisation of Continuous Schedules

In this section, a method of transforming the continuous pump schedules obtained by non-linear programming into discrete schedules is described. Let τ_c denote time step for continuous pump schedules and τ_d denote time step for discrete pump schedules, also τ_d represents the minimum time before the pump changing its status. Define sp_i^j as switching period i for pump station $j \in J_p$. Switching period is a time step in which the pump can change it status "ON/OFF" or "OFF/ON" only one time and is estimated by equation (8.6). Figure 8.3 schematically illustrates the terms of continuous and discrete time steps and switching period.

$$sp = \frac{24 \times 60}{\text{maximum allowed number of switching}} [\text{min}] \tag{8.6}$$

Let $\phi_{k_c}^j$ and $\psi_{k_d}^j$ denote total flow through pump station j obtained for continuous and discrete schedule, respectively. k_c and k_d are the indices of continuous and discrete time step, respectively and where

$$\text{time}(k_c + 1) - \text{time}(k_c) = \tau_c \tag{8.7}$$

and

$$\text{time}(k_d + 1) - \text{time}(k_d) = \tau_d \tag{8.8}$$

Continuous schedules consist of a set of pump station control vectors $c_{k_c}^j$, each consisting of number of pumps being "ON" $u_{k_c}^j$ and pump speed $s_{k_c}^j$, where $u_{k_c}^j$, $s_{k_c}^j \in \mathbb{R}$; $u_{k_c}^j$, $s_{k_c}^j \geq 0$. Continuous schedules cannot be directly implemented in such form (it is not physically possible to have e.g. "0.3 of pump "ON"), thus require further processing. The goal of schedules discretisation process is to produce a set of equivalent control vectors denoted $\tilde{c}_{k_d}^j$ each consisting of number of pumps being "ON" $\tilde{u}_{k_d}^j$ and pump speed $\tilde{s}_{k_d}^j$, where $\tilde{s}_{k_d}^j \in \mathbb{R}$; $\tilde{s}_{k_d}^j \geq 0$ and $\tilde{u}_{k_d}^j \in \mathbb{N}$, $\tilde{u}_{k_d}^j \geq 0$. Such discrete schedules can directly be implemented in the network.

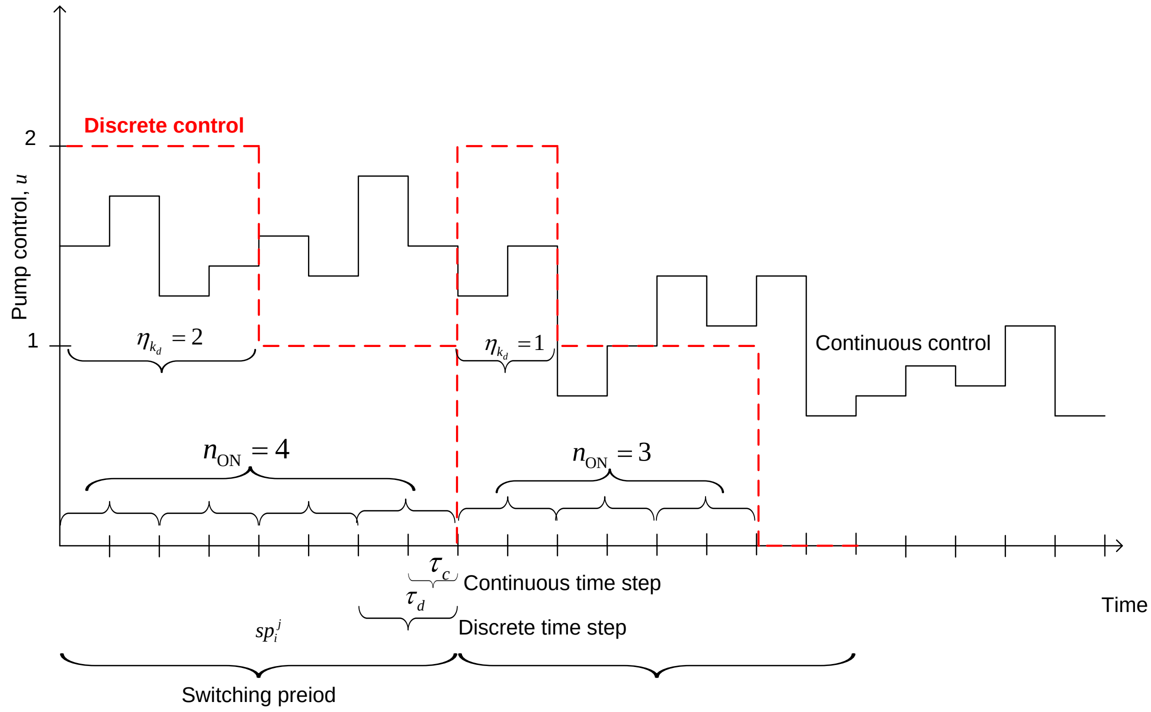


Figure 8.3 Schematic of discretisation terminologies

Proposed schedules discretisation approach is based on concept of matching pump flows resulting from discrete schedule to pump flows resulting from continuous schedule, for each pump and each switching period. Formally, the approach attempts to generate such discrete schedules that satisfy:

$$\phi^j\left(sp_{i,j}\right) \approx \psi^j\left(sp_{i,j}\right) \tag{8.9}$$

Assumptions for the considered approach are stated as follows:

1. Time steps for continuous and discrete pump schedules are such that

$$\tau_d = n \cdot \tau_c,\ n \geq 1\ \forall\ n \in \mathbb{N}$$

and

$$sp = n_d \cdot \tau_d = n_c \cdot \tau_c \quad \forall \;\; n_c, n_d \in \mathbb{N}$$

where n is the number of continuous time steps in one discrete time step. n_c and n_d are number of continuous time steps and number of discrete time steps in one switching period, respectively.

2. Pump speeds $\tilde{s}_{k_d}^{j}$ and $s_{k_c}^{j}$ are the same during corresponding periods.

Note that second assumption imposes that condition given by equation (8.9) needs to be achieved by manipulating number of pumps being "ON" in a given pump station, rather than by manipulating their speed. The reason for such assumption is that power consumption increases significantly when the pump speed is increased to maintain at least the same delivered flow and head, as depicted in equation(8.2).

The algorithm of discretisation consists of two overlapped interdependent stages. In the first stage, for a given pump station and a switching period, the number of consecutive discrete time steps (n_{ON}) (over which pumps being "ON") is computed, Figure 8.3 illustrates the variable n_{ON}. In the second stage, the number of pumps ($\tilde{u}_{k_d}^{j}$) that should be switched "ON" over the n_{ON} consecutive discrete time steps is estimated. The two stages are depending on each other because the number of discrete time steps, n_{ON}, depending on the pumped flow which depends on the number of pumps being "ON". n_{ON} is computed by equation (8.10).

$$n_{\text{ON}} = \text{round}\left(\frac{\tau_c \sum_{i_c=1}^{n_c} \phi_{i_c}^{j} + \delta^{j}\left(sp_{i-1,j}\right)}{\dfrac{\tau_d}{n_{\text{ON}}} \sum_{i_c=1}^{n_d} \psi_{i_d}^{j}} \right) = \text{round}\left(\frac{\phi^{j}\left(sp_{i,j}\right) + \delta^{j}\left(sp_{i-1,j}\right)}{\bar{\psi}^{j}} \right) \tag{8.10}$$

where $\phi^{j}\left(sp_{i,j}\right) = \tau_c \sum_{i_c=1}^{n_c} \phi_{i_c}^{j}$ is the total continuous pumped flow in one switching period. $\bar{\psi}^{j} = \dfrac{\tau_d}{n_{\text{ON}}} \sum_{i_c=1}^{n_d} \psi_{i_d}^{j}$ is the average discrete pumped flow in one switching period. $\delta^{j}\left(sp_{i-1,j}\right)$ is the difference between the continuous and discrete flow for the previous switching period. This term has been added to minimize the accumulated error (the difference between total discrete flow and total continuous flow) over the entire time horizon. $\delta^j\left(sp_{i,j}\right)$ for any switching period i for a pump station j is estimated by the equation below

$$\delta^j\left(sp_{i,j}\right)=\phi^j\left(sp_{i,j}\right)-\psi^j\left(sp_{i,j}\right) \tag{8.11}$$

As illustrated in equation (8.10) the value of n_{ON} is not given explicitly as it appears in the both side of the equation, therefore an iterative technique has been used to compute its value. To be able to compare $\phi^j\left(sp_{i,j}\right)$ and $\psi^j\left(sp_{i,j}\right)$ network hydraulic simulator has been utilised.

In the discretisation algorithm, pump stations with one duty pump or $u_{k_c}^j<1$ have been treated differently than the pump stations with more than one duty pump and $u_{k_c}^j>1$ as discussed below.

For pump stations with one duty pump or $u_{k_c}^j<1$, the minimum number of pumps being "ON" is 0 and the maximum is 1. Over the number of consecutive discrete time steps (n_{ON}), the control variable $\tilde{u}_{k_d}^j=1$ and outside this interval $\tilde{u}_{k_d}^j=0$ and during the iterative solution only the variable n_{ON} is changed to adjust the discrete pump flow to match the continuous flow. While for pump station with more than one duty pump and $u_{k_c}^j>1$, the maximum and minimum number of pumps being "ON" are calculated as $\operatorname{ceil}\left(u_{k_c}^j\right)$ and $\operatorname{integer}\left(u_{k_c}^j\right)$, respectively, where $\operatorname{ceil}\left(u_{k_c}^j\right)$ denotes $u_{k_c}^j$ rounded up and $\operatorname{integer}\left(u_{k_c}^j\right)$ denotes integer part of $u_{k_c}^j$. Such maximum and minimum are imposed so that the discrete schedules are 'close' to the continuous schedules. So initially, over the number of consecutive discrete time steps (n_{ON}), the control variable $\tilde{u}_{k_d}^j=\operatorname{integer}\left(u_{k_c}^j\right)$ and outside this interval $\tilde{u}_{k_d}^j=0$. Knowing that at least $\operatorname{integer}\left(u_{k_c}^j\right)$ pumps are being "ON", it needs to decide whether an additional pump should be added, that is whether $\tilde{u}_{k_d}^j=\operatorname{integer}\left(u_{k_c}^j\right)$ or $\tilde{u}_{k_d}^j=\operatorname{ceil}\left(u_{k_c}^j\right)$, over a number of discrete time steps

For pump station with more than one duty pump and $u_{k_c}^j>1$, define η_{k_d} as the number of discrete time steps when an additional pump is required to match the discrete pump flow with the continuous pump flow over one switching period. Value of η_{k_d} is calculated based on the difference between the delivered discrete flow by $\text{integer}\left(u_{k_c}^j\right)$ pumps and the continuous flow as follows:

$$\eta_{k_d} = \text{round}\left(\frac{\psi^j\left(sp_{i,j}\right)\Big|_{\text{integer}\left(u_{k_c}^j\right)} - \phi^j\left(sp_{i,j}\right)}{\bar{\psi}^j\Big|_{\text{Additional Pump}}}\right) \tag{8.12}$$

where $\psi^j\left(sp_{i,j}\right)\Big|_{\text{integer}\left(u_{k_c}^j\right)}$ is the total discrete flow delivered by $\text{integer}\left(u_{k_c}^j\right)$ pumps over consecutive discrete time steps (n_{ON}), and $\bar{\psi}^j\Big|_{\text{Additional Pump}}$ is the average discrete flow delivered by an additional pump in a discrete time step.

Having $\eta_{k_d} > 0$, it needs to be decided to which discrete time steps an additional pump is assigned. Here, the additional pump has been assigned to the consecutive first discrete time steps in the switching period.

As depicted in equation (8.12) the value of η_{k_d} is dependent on the pump flows which in turn depend on the hydraulic characteristics of the network, therefore an iterative technique has been used to compute its value by utilizing a network simulator.

Remark 2. *Solution of continuous optimisation problem is often such, that the results hit constraints (typically that of maximum and minimum allowed reservoir level), i.e. are on the border of feasibility. Therefore, discretisation of continuous schedules may result in minor violation of these constraints.*

Further details on implementation of the proposed pump schedules discretisation are given in the section below.

8.4.1 Software implementation

The proposed discretisation algorithm has been implemented in Matlab environment. Developed user interface (illustrated in Figure 8.4) allows the user to: manipulate the discrete schedule generated by the algorithm for each pump, export the schedule back to

Epanet, load simulation results from Epanet, evaluate $\phi^j\left(sp_{i,j}\right)$ and $\psi^j\left(sp_{i,j}\right)$ for each pump at each switching period.

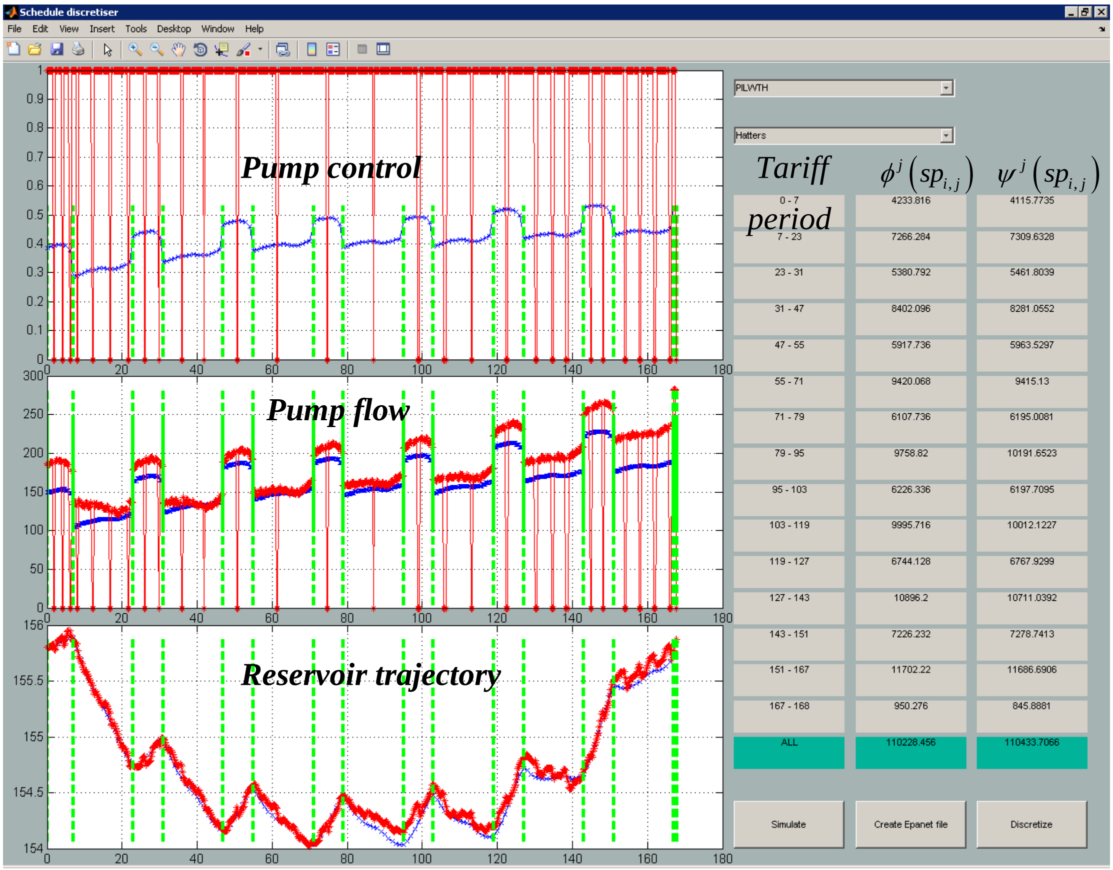


Figure 8.4 User interface for schedules discretiser software

8.5 Case Study

The application of continuous optimal pump schedule and the discretisation algorithm have been applied to a case study of Oldham water supply system provided by United Utilities. Detailed information about the network of Oldham water supply system is attached in Appendix B. In addition, a model description and simplification are also discussed. The results of the case study showed the functionality and the reliability of the developed algorithms.

The schematic diagram of Oldham water supply system, Figure 8.5, shows the locations of pump stations, service reservoirs and water treatment works (WTW) in the system. Oldham water system is supplied by water from four WTW, and four feeds from Haweswater Aqueduct / Manchester ring main to feed 45 DMAs of 63.2 Ml/d daily demand and gravity fed from the service reservoirs.

Table 8.2 shows a brief summary of the different components included in Oldham WDS. The hydraulic Epanet and Finesse models, GAMS code and CONOPT output result file of this case study are provided in the enclosed CD, file descriptions, paths and locations are listed in Appendix D.

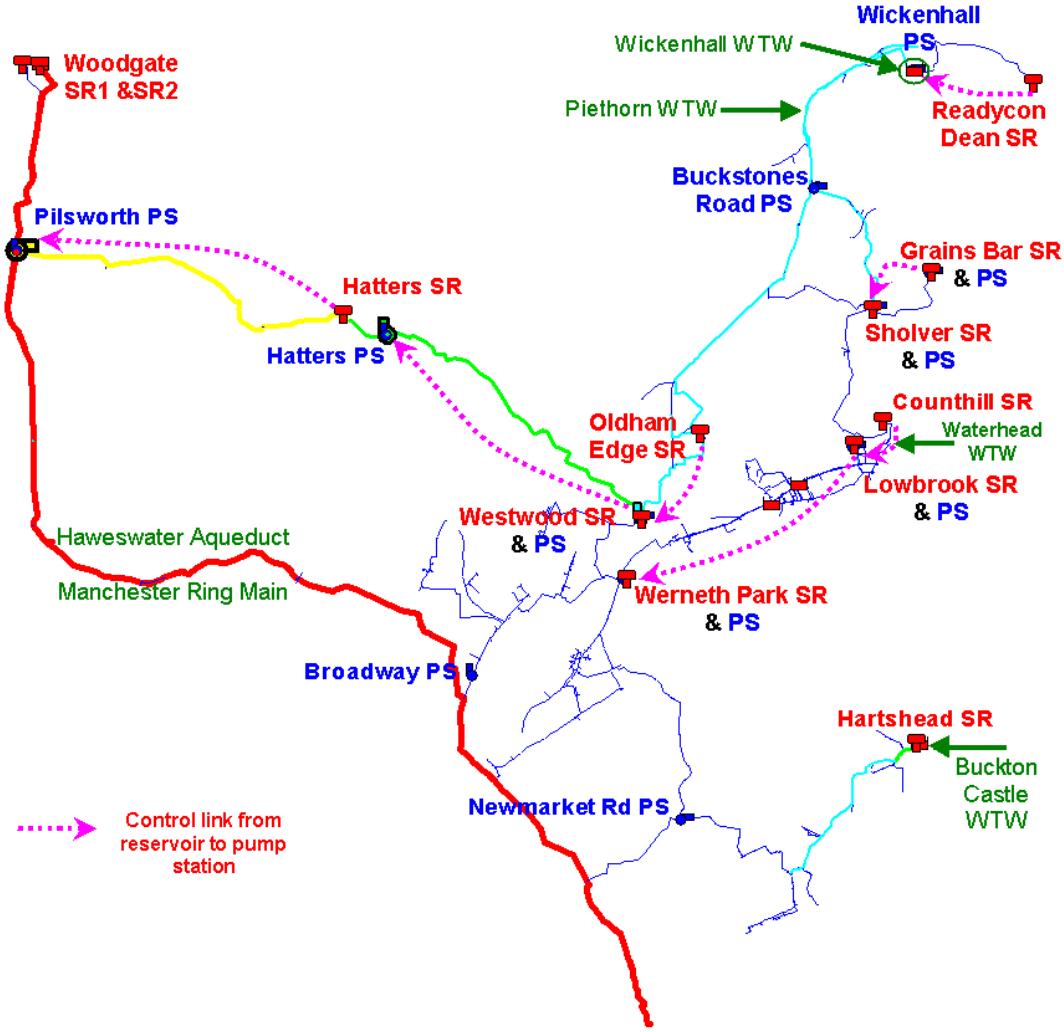


Figure 8.5 Network of Oldham water supply system depicts the pump stations controlled by downstream reservoirs water level and the locations of water treatment works (WTW)

Table 8.2. Oldham model summary

Components	Number
Junctions	3535
DMAs	45
Fixed head reservoirs	5
Variable head tanks	12
Pipes	3279
Pump stations	11 includes 19 pumps 7 VSP + 12 FSP
Valves	418 2 Flow control valve 1 Pressure reducing valve 12 Pressure sustaining valve 403 Throttle control valve

Oldham system contains six variable speed drive pump stations and five fixed speed pump stations, all pump stations in the system are scheduled except Broadway pump station which is out of service and Grains Bar which is a booster pump. Table 8.3 shows the pump station and the corresponding upstream and downstream reservoirs, as well the drive type and number of pumps. All pump stations in the system have only one duty pump except sholver PS that has two duty pumps.

Table 8.3 Data of the pump station in Oldham water supply system

Pump Station	No. of pumps	Type of drive*	Upstream reservoir	Downstream reservoir
Hatters PS	2	VSD	Hatters SR	Westwood SR
Westwood PS	2	VSD	Westwood SR	Oldham Edge
Broadway PS†	1	FSD	Haweswater Aqueduct	
Werneth Park PS	1	VSD	Werneth Park SR	Lowbrook RS
Grains Bar‡	1	VSD	Grains Bar	
Sholver PS	3	FSD	Sholver SR	Grains Bar
Wickenhall PS	2	FSD	Wickenhall WTW	Readycon Dean
Bucktones Road PS	2	FSD	Piethorn WTW_	
Lowbrook PS	2	FSD	Lowbrook SR	Counthill RS
Pilsworth PS	2	VSD	Haweswater Aqueduct	Hatters SR
Newmarket Rd PS	1	VSD	Haweswater Aqueduct	Werneth Park SR

* *FSD stand for fixed speed drive, VSD stand for variable speed drive.*
† Broadway PS is no longer in services
‡ Grains Bar is a booster pump.

The hydraulic and power characteristics of all pump stations have been attached in Appendix B.

Table 8.4 summarizes the elevations, capacities and water costs for water sources of Oldham water supply system.

Table 8.4. Water sources of Oldham supply system

Water Sources	Elevation [m]	Capacity [Ml/day]	Cost £/Ml
Piethorn WTW	257	17	25
Wickenhall WTW	300	10	33
Waterhead WTW	212	14	27
Buckton Castle WTW	216.2	14- to Oldham, 48- total capacity	25
Haweswater Aqueduct	~140 – Average head	~17 to Oldham ~325 – Total flow	57

Oldham water supply system comprises ten service reservoirs with different dimensions and capacity, as shown in Table 8.5.

Table 8.5 Data of the service reservoirs in Oldham supply system◙

Reservoir Name	Elevation	TWL† [m]	Diameter* [m]	Volume [Ml]
Hartshead SR	189	6.1	86.68	36
Hatters SR	151.47	6.42	69.42	24.3
Westwood SR	158.6	6	67.37	21.39
Werneth Park SR	158.9	5.7	50.46	11.4
Sholver SR	274.4	7.1	44.62	11.1
Readycon Dean SR	374.6	4	19.54	1.2
Grains Bar SR	352.2	5.8	36.59	6.1
Counthill SR	267.3	5.8	51.11	11.9
Lowbrook SR	228.8	6.2	66.91	21.8
Oldham Edge SR	219.8	7	70.47	27.3

◙ *Data within this table was extracted from the hydraulic model*
* *Equivalent hydraulic diameter*
† *Top water level (TWL) is the physical limit of the reservoir*

The electrical cost is the consumption charge (£/kWh), i.e., the cost of electrical energy consumed during a time period. In this study, summer tariff has been used to calculate the pumping cost, hence the demand and telemetry data are provided for the first week of August 2007. Electricity tariff on the summer week day, illustrated in Figure 8.6, has two different rate per day, off-peak and peak tariffs. The peak tariff period of 7.753 p/kWh extends from 07:00 to 23:00 of electricity cost, while the off-peak tariff of 6.204 p/kWh covers the rest of the day and extends from 23:00 to 07:00.

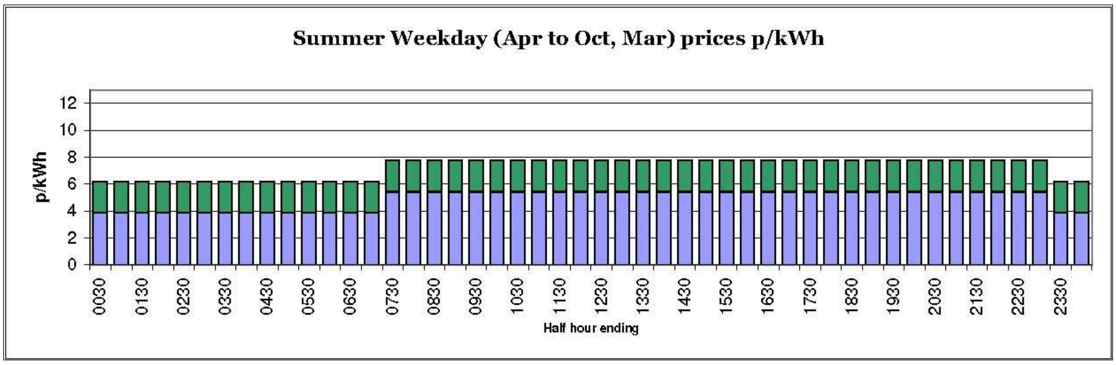


Figure 8.6 Summer electricity tariff for 2008/2009

8.5.1 Elements and components to be scheduled

The elements and components that have been scheduled in this case study are eight pump stations, two valves and three water treatment works.

8.5.1.1 Pump stations

Table 8.6 shows the pump stations that have been scheduled, the variable speed pumps have been optimized to run between 50% and 100% of the rated speed, and the minimum time before changing its status (setpoint change time) is 30 minutes.

Table 8.6 Pump stations to be scheduled

Pump Station	No. of pumps	Type of driver*
Hatters PS	2	variable speed
Westwood PS	2	variable speed
Werneth Park PS	1	variable speed
Newmarket Rd PS	1	variable speed
Sholver PS	3	fixed speed
Wickenhall WTW	2	fixed speed
Lowbrook PS	2	fixed speed
Pilsworth PS	2	variable speed
Bucktones Rd PS	2	fixed speed

8.5.1.2 Water treatment works

Wickenhall WTW has a constant rate of water production of 10 Ml/d and has not been scheduled. The imported flow from Haweswater Aqueduct (Manchester main ring) should be minimized due to its high cost. Table 8.7 shows the information about water treatment works that have been scheduled. There is a generic ramp-up rate of 1 Ml/d/d i.e. consecutive daily average productions are within 1 Ml/d, which has been taken into account.

It is difficult to optimise the total output from Buckton Castle WTW without modelling the rest of the Rochdale system, therefore, a partial output of Buckton Castle WTW, which feeds the Oldham system has been optimised with a maximum limit of 14 Ml/d.

Table 8.7 The water treatment works costs and limits

	Cost £/Ml	Capacity Ml			Ramp-up rate Ml/d/d
		Min	Max	Reliable yield	
Piethorne	25	10	20	6.55	1
Waterhead	27	7	14	7.62	1

8.5.1.3 Valves

Two valves have been optimised in this case study as shown in Table 8.8

- Valve on the pipe between Sholver SR and Counthill SR,
- Coalpit Lane transfer valve.

The Coalpit Lane transfer valve, between Tameside and Oldham networks, has been optimised using an upper limit of 14Ml/d. The cost for this water is the same as the Buckton Castle costs. Table 8.8 summarises the valves setting.

Table 8.8 Scheduled valves setting

Valve ID	**OLDH0039**	**X2419973_**
Start Node	316T1003	24199003
End Node	31600001	0020748C
Description	Supply Meter 46868 Coal Pit Lane Transfer - Partially open valve with Tau 0.04 and coefficient 1	Partially open valve with Tau 0.005 and coefficient 0.12
Diameter	380	533
Type	TCV	TCV
Setting	625	4800
Loss Coeff.	1	0.12

Leakage in main trunk lines has been taken into account, by adding 6.25 Ml/d (10% of total DMA daily demand) pressure dependent leakage under current operating pressure and removing the current constant leakage from the provided hydraulic model. PRVs scheduling is not possible, pump and PRV in series without reservoir in line is not available in the current case study.

8.6 Results and Discussion

Different cases have been solved to test and evaluate the developed algorithm of continuous pump schedule and the algorithm of discretisation.

- Optimizing pump schedules, valve flows and source flows over 24 hr
- Optimizing pump schedules and valve flows over 24 hr
- Optimizing pump schedules and valve flows over 7 days

The scenarios have been solved by assuming initial reservoirs levels and lower and upper constraints as depicted in Table 8.9.

Table 8.9 Reservoirs levels and constraints in [m]

Reservoir	**Elevation**	**Full range**	**Initial level**	**Minimum water level Constraint**	**Maximum water level Constraint**
			(Min+Max)/2	40 % of full range	95 % of full range
Hatters SR	151.47	6.42	4.33	2.568	6.1
Westwood SR	158.6	6	4.05	2.4	5.7
Werneth Park SR	158.9	5.7	3.85	2.28	5.42
Hartshead SR	189	6.1	4.12	2.44	5.8
Oldham Edge SR	219.8	7	4.73	2.8	6.65
Lowbrook SR	228.8	6.2	4.19	2.48	5.89
Counthill SR	267.3	5.8	3.92	2.32	5.51
Sholver SR	274.4	7.1	4.79	2.84	6.75
Grains Bar SR	352.2	5.8	3.92	2.32	5.51
Readycon Dean SR	374.6	4	2.7	1.6	3.8

The results of optimal pump schedule algorithms have been compared with the current operation in terms of pumping energy and costs. Continuous and discrete solutions for pump controls, pump flows, valve flows, and reservoir trajectories are presented to compare between two solutions.

8.6.1 Optimizing pumps schedule, valves flow and source flow over 24 hours "Case 1"

In this scenario, the problem has been solved over 24 hr to optimise the pump schedule, valve flow and water sources. The final reservoirs levels are set to be at least as the initial levels. The running time for this scenario was 6.5 min for the continuous solution and 4 min for the discrete solution.

8.6.1.1 Continuous and discrete pump schedule

Figure 8.7-8.9 show the continuous and discrete pump controls, flows, and speed for variable speed pumps. The pump stations Lowbrook and Werneth Park were OFF in this scenario.

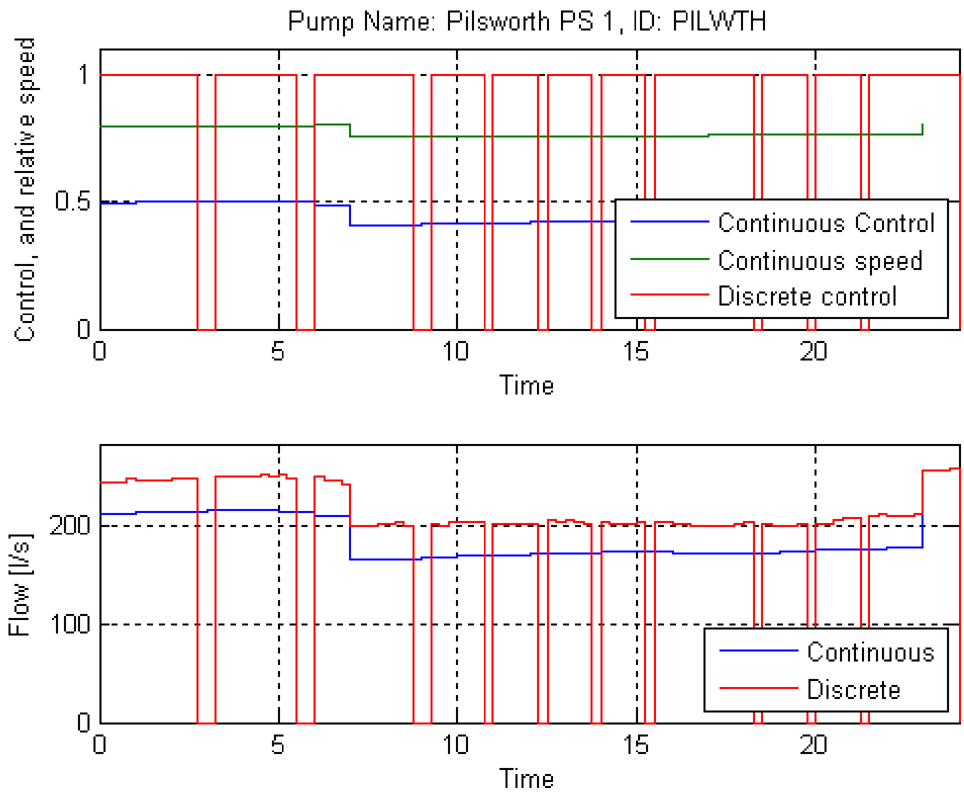


Figure 8.7 Continuous and discrete pump schedule for Pilsworth PS

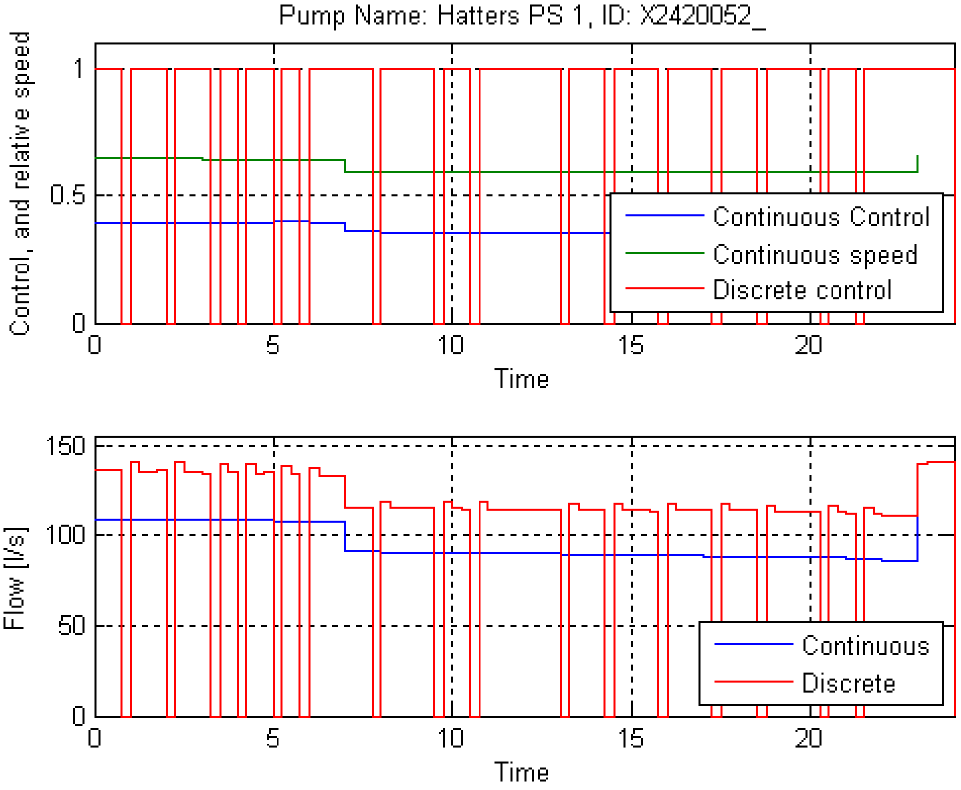


Figure 8.8 Continuous and discrete pump schedule for Hatters PS

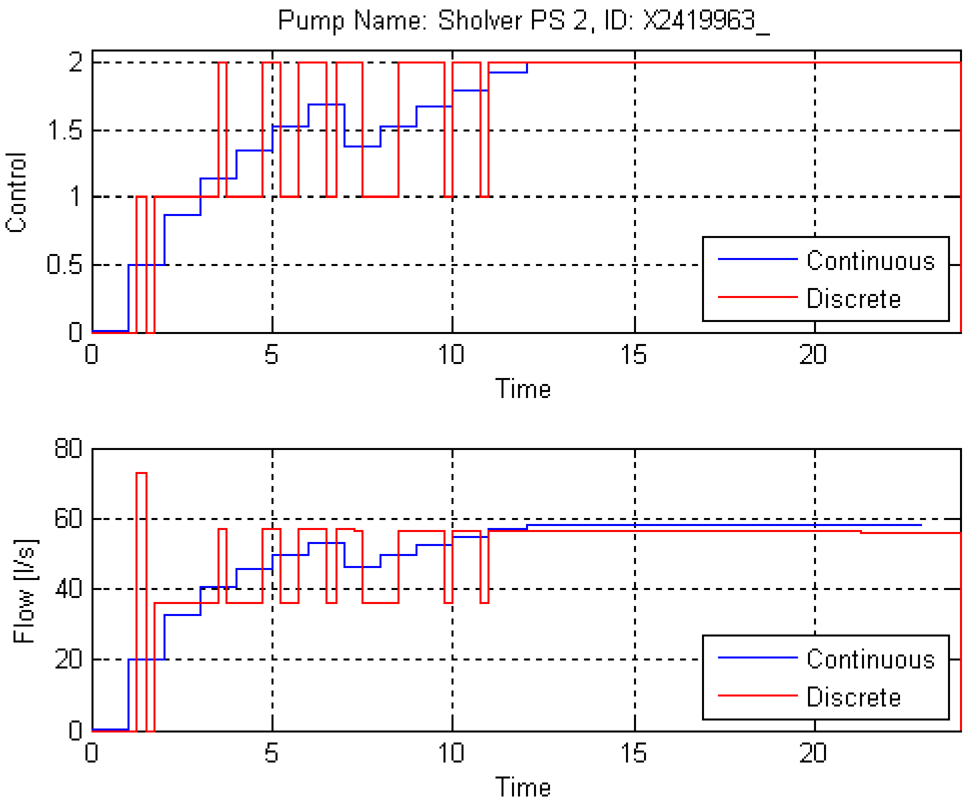


Figure 8.9 Continuous and discrete pump schedule for Sholver PS

8.6.1.2 Continuous and discrete reservoir trajectories

Figure 8.10 illustrates the reservoir trajectories for the optimal continuous and the discrete solutions of the pump schedule problem. The upper red and lower green straight lines represent the upper and lower reservoir bounds. Both trajectories show good matches as depicted in the figure which indicates that the continuous and discrete pumps flows are similar as suggested by equation(8.9).

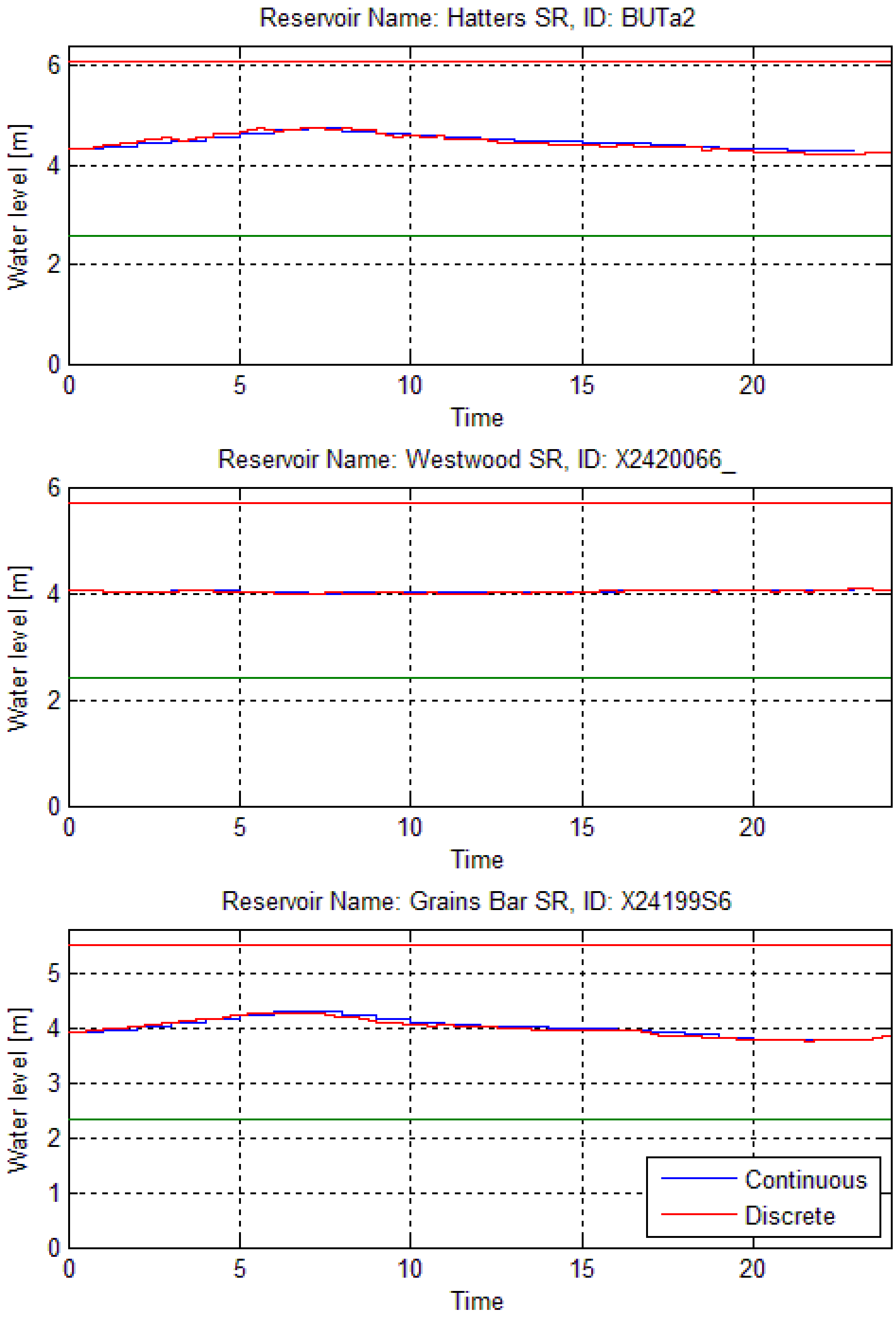


Figure 8.10 Continuous and discrete reservoir trajectories

8.6.1.3 Valve flows of continuous and discrete schedules

The figure below illustrates the continuous and discrete flows for the Chapel Rd and Sholver-Counthill valves. Both flows of Sholver-Counthill valve are identical, while discrete flow of Chapel Rd is lower than the continuous one in the periods of Newmarket Rd PS being "OFF".

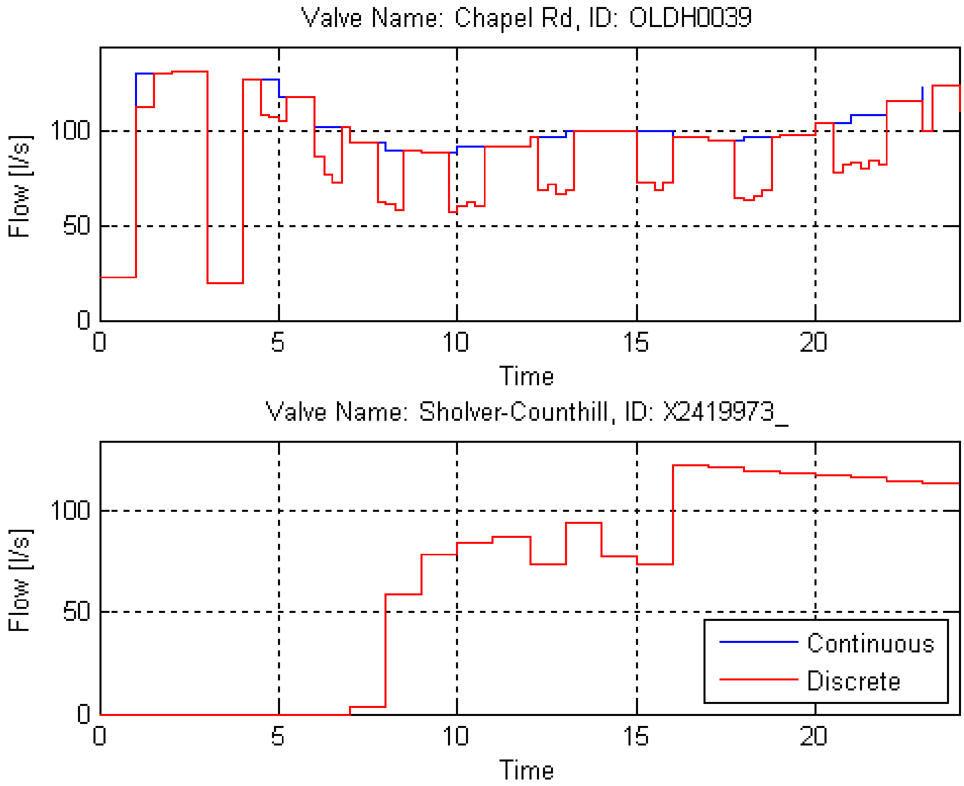


Figure 8.11 Valves flow of continuous and discrete schedules

8.6.1.4 Comparison of the current operation and the optimal schedule

To compare overall performance of the optimisation algorithms, the total final mass balance of the reservoirs is defined as the difference between the final total water volume in all reservoirs and the initial total water volume in all reservoirs. The total final mass balance has been computed and shown in Table 8.10, together with pumping energy and total pumping cost which calculated for the optimal schedule and the current operations shown in Table 8.11. Due to the imposed constraints for the final reservoirs water level, the total final mass balance of 0.6 Ml is very small. The total saving in pumping energy and pumping cost are 56.5% and 58.2% respectively, which is considered very high. This high savings in pumping energy and cost are due to optimizing source flows of Waterhead WTW and Piethorn WTW to maximum capacities. These two WTWs feed Oldham Edge SR and Lowbrook SR by gravity, which reduces the flow from Haweswater Aqueduct through the pump stations Pilsworth, Hatters, Westwood, and Werneth Park, which in turns reduces the pumping energy and cost significantly.

Table 8.10 Reservoir mass balance [Ml]

Reservoir name	Current Operation	Optimal Schedule
Hartshead SR	-0.86	0.81
Hatters SR	2.11	-0.20
Westwood SR	0.39	0.03
Werneth Park SR	-1.36	-0.10
Sholver SR	-0.42	0.18
Readycon Dean SR	-0.09	-0.01
Grains Bar SR	-1.51	-0.05
Counthill SR	2.98	-0.02
Lowbrook SR	-0.90	0.25
Oldham Edge SR	6.88	-0.28
Total	7.21	0.6

Table 8.11 Pumping Energy and cost

	Pumping Energy [KWhr]			Pumping cost [£]	
Pump name	**Current operations**	**Optimal Schedule**		**Current operations**	**Optimal Schedule**
Hatters PS 1	3338.05	629.98		241.57	45.1
Hatters PS 2	0	0		0	0
Westwood PS 1	0	0		0	0
Westwood PS 2	2389.62	889.11		173.71	55.53
Broadway PS	0	0		0	0
Werneth Park PS	1900.94	0		137.49	0
Grains Bar PS	0	0		0	0
Sholver PS 1	495.73	88.47		37.15	5.49
Sholver PS 2	495.81	1696.98		37.15	122.1
Sholver PS 3	0	0		0	0
Wickenhall PS 1	0	0		0	0
Wickenhall PS 2	188.29	147.09		14.40	9.87
Bucktone Rd PS 1	0	0		0	0
Bucktone Rd PS 2	0	731.43		0	50.45
Lowbrook PS 1	1096.30	0		79.72	0
Lowbrook PS 2	0	0		0	0
Pilsworth PS 1	4190.28	1487.5		303.05	106.37
Newmarket Rd PS	0	464.88		0	33.42
Pilsworth PS 2	0	0		0	0
Total [KWhr]	14095.03	6135.44	**Total [£]**	1024.24	428.31
saving [KWhr]		**7959.59**	**saving [£]**		**595.93**
saving [%]		**56.47**	**saving [%]**		**58.18**

The optimal schedule has also reduced the pressure dependent leakage as depicted in Table 8.12.

Table 8.12 Leakage flow [Ml]

	Current operations	**Optimal Schedule**
Total [Ml]	6.25	6.12
saving [Ml]		0.14
saving [%]		2.21

8.6.2 Optimizing pumps schedules and valve flows over 24 hr "Case 2"

To evaluate the benefits of the optimal pump schedule the previous scenario has been solved again but without optimising water sources, and the corresponding sets of results are presented.

8.6.2.1 Continuous and discrete pump schedule

Figure 8.12-8.14 show the continuous and discrete pump controls, flows, and speed for variable speed pumps.

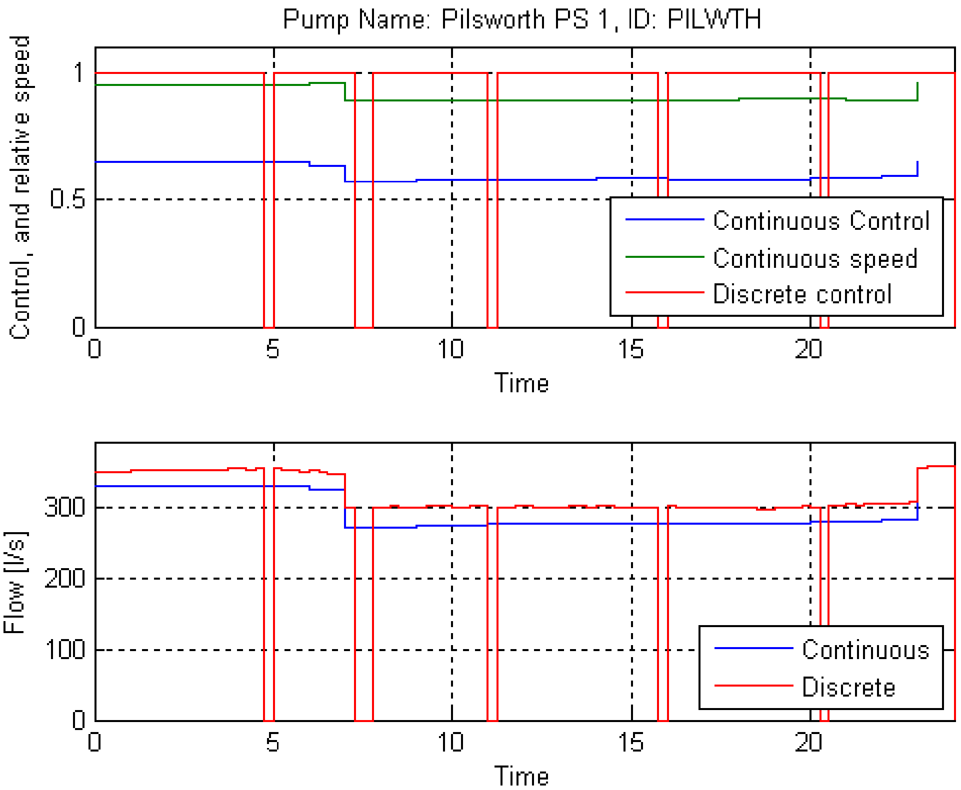


Figure 8.12 Continuous and discrete pump schedule for Pilsworth PS

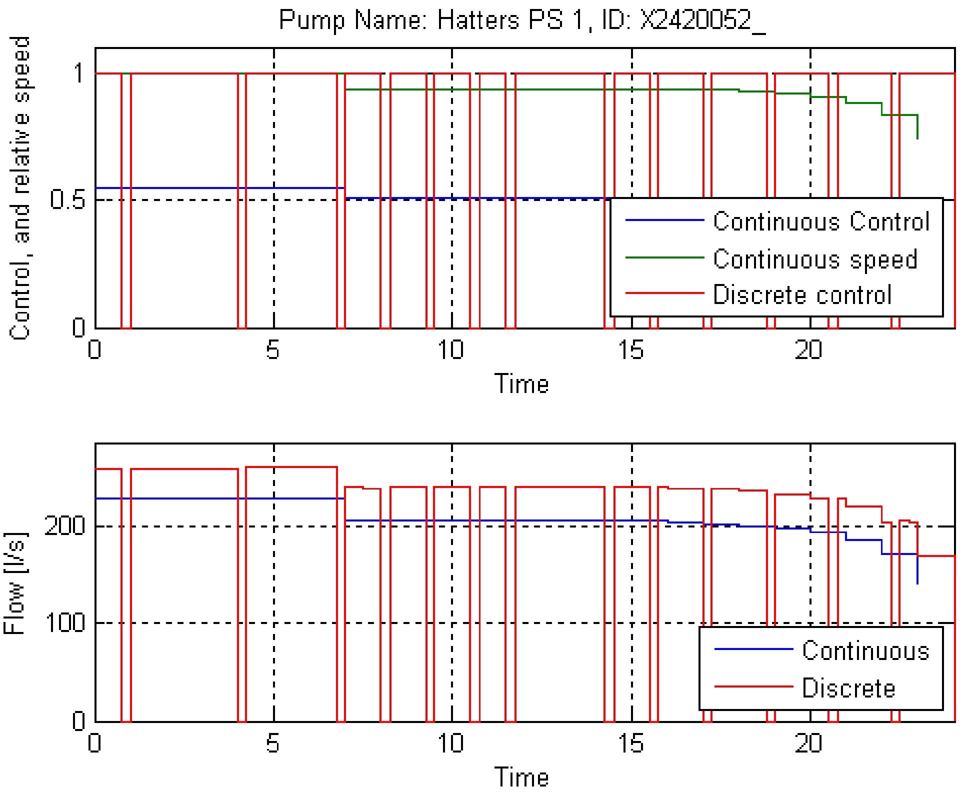


Figure 8.13 Continuous and discrete pump schedule for Hatters PS

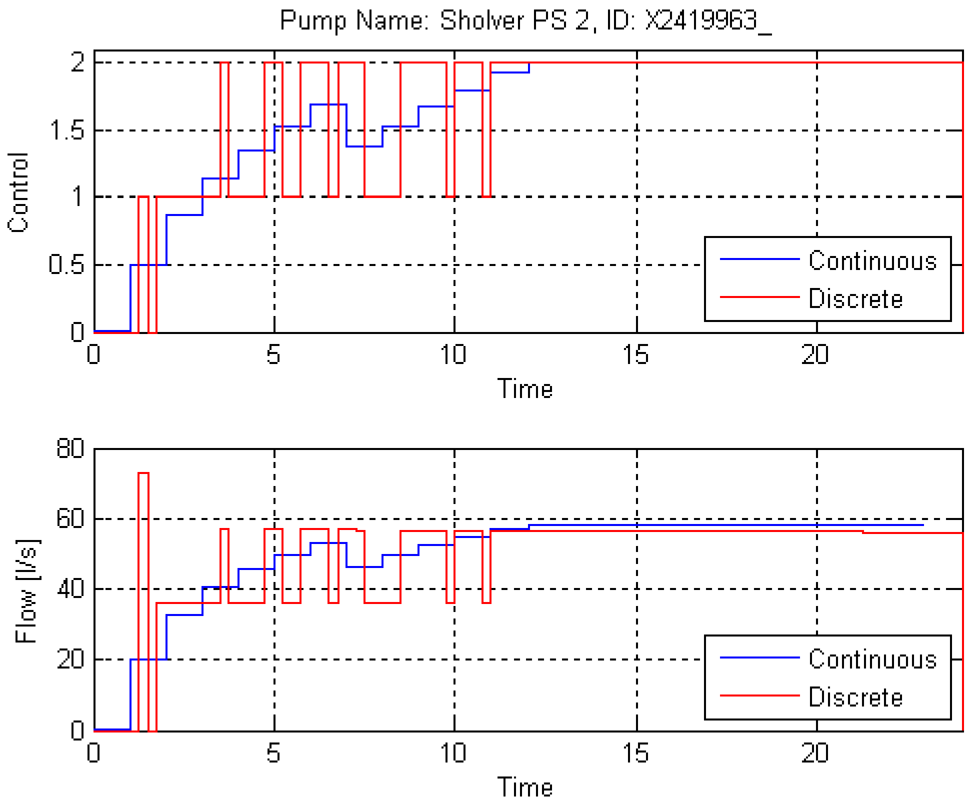


Figure 8.14 Continuous and discrete pump schedule for Sholver PS

8.6.2.2 Continuous and discrete reservoir trajectories

Figure 8.15 illustrate the reservoir trajectories for the optimal continuous and the discrete solutions of the pump schedule problem. The upper red and lower green straight lines represent the upper and lower reservoir bounds. Both trajectories show good matches as depicted in the figure which indicates that the continuous and discrete pumps flows are similar as suggested by equation(8.9).

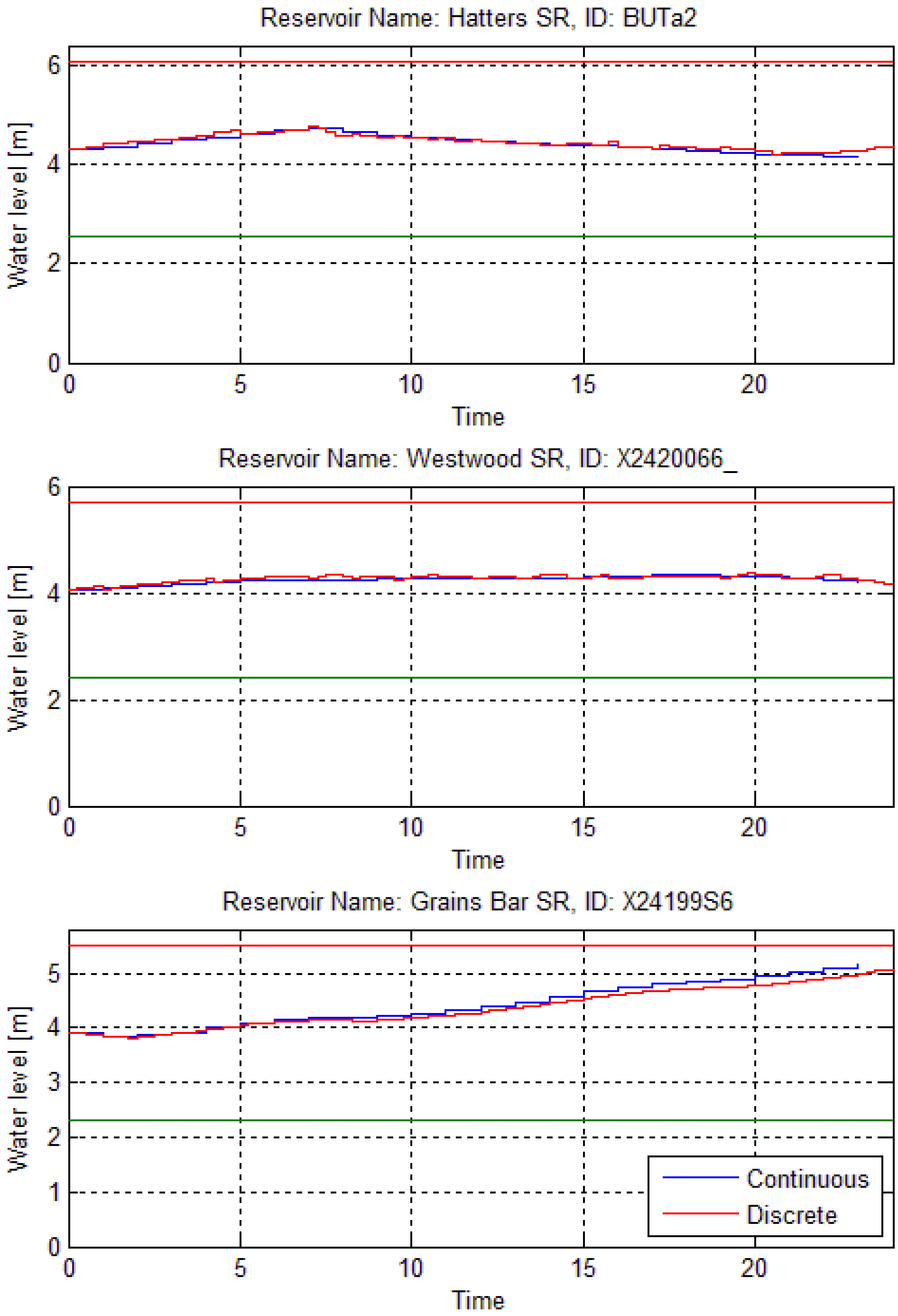


Figure 8.15 Continuous and discrete reservoir trajectories

8.6.2.3 Valves flow of continuous and discrete schedules

Figure 8.16 illustrates the continuous and discrete flows for the Chapel Rd and Sholver-Counthill valves. Both flows of Sholver-Counthill valve are identical, while discrete flow of Chapel Rd is lower than the continuous one in the periods of Newmarket Rd PS being “OFF”.

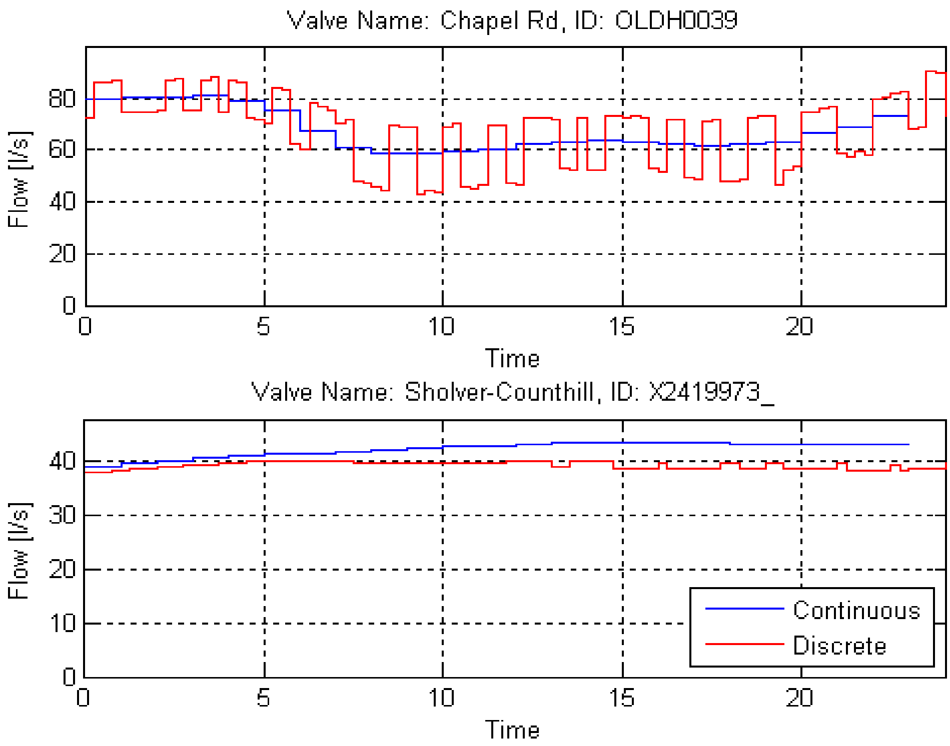


Figure 8.16 Valves flow of continuous and discrete schedules

8.6.2.4 Comparison of the current operation and the optimal schedule

Table 8.13 illustrates the final mass balance of each reservoir and the total final mass balance which is 4.2 Ml for the optimal schedule. In this scenario, the total saving in pumping energy and cost are 10.2% and 11.4% respectively, as shown in Table 8.14.

Table 8.13 Reservoir mass balance [Ml]

Reservoir name	Current Operation	Optimal Schedule
Hartshead SR	-0.86162	0.994083
Hatters SR	2.108643	0.294032
Westwood SR	0.391173	0.350103
Werneth Park SR	-1.36438	-0.0061
Sholver SR	-0.41962	1.343912
Readycon Dean SR	-0.09218	-0.02324
Grains Bar SR	-1.50983	1.243274
Counthill SR	2.978406	-0.15791
Lowbrook SR	-0.8955	0.006653
Oldham Edge SR	6.878261	0.190549
Total	7.213353	4.235353

Table 8.14 Pumping Energy and cost

	Pumping Energy [KWhr]			**Pumping cost [£]**	
Pump name	**Current operations**	**Optimal Schedule**		**Current operations**	**Optimal Schedule**
Hatters PS 1	3338.045	2417.888		241.5685	173.1456
Hatters PS 2	0	0		0	0
Westwood PS 1	0	0		0	0
Westwood PS 2	2389.622	1916.621		173.7091	132.6725
Broadway PS	0	0		0	0
Werneth Park PS	1900.944	785.5588		137.4908	54.10281
Grains Bar PS	0	0		0	0
Sholver PS 1	495.7263	1217.611		37.14585	91.39184
Sholver PS 2	495.8115	1633.418		37.15226	118.992
Sholver PS 3	0	0		0	0
Wickenhall PS 1	0	0		0	0
Wickenhall PS 2	188.2941	184.1796		14.40052	13.43398
Bucktone Rd PS 1	0	0		0	0
Bucktone Rd PS 2	0	903.5297		0	64.45819
Lowbrook PS 1	1096.302	393.7133		79.72259	29.77212
Lowbrook PS 2	0	0		0	0
Pilsworth PS 1	4190.28	2921.669		303.0462	208.318
Newmarket Rd PS	0	286.7535		0	20.81257
Pilsworth PS 2	0	0		0	0
Total [KWhr]	14095.03	12660.94	**Total [£]**	1024.236	907.0996
saving [KWhr]		1434.084	**saving [£]**		117.1362
saving [%]		10.1744	**saving [%]**		11.43645

In addition, the pressure dependent leakage is reduced in this scenario by 4% as depicted in Table 8.15.

Table 8.15 Leakage flow [Ml]

	Current operations	Optimal Schedule
Total [Ml]	6.254078	6.001659
saving [Ml]		0.252419
saving [%]		4.036072

8.6.3 Optimizing pump schedules and valve flows over 7 days “Case 3”

Optimizing 7 days of operation makes the solver to utilize the water volume in the reservoirs, which gives opportunity for more saving in pumping energy and cost. In 7 days scenario, the pumps schedule and valve flows are optimized under the same constraints on reservoirs and the same initial and final states as in the previous scenarios, and the corresponding sets of results are presented below.

8.6.3.1 Continuous and discrete pump schedule

Figure 8.17 - 8.19 show the continuous and discrete pump controls, flows, and speed for variable speed pumps.

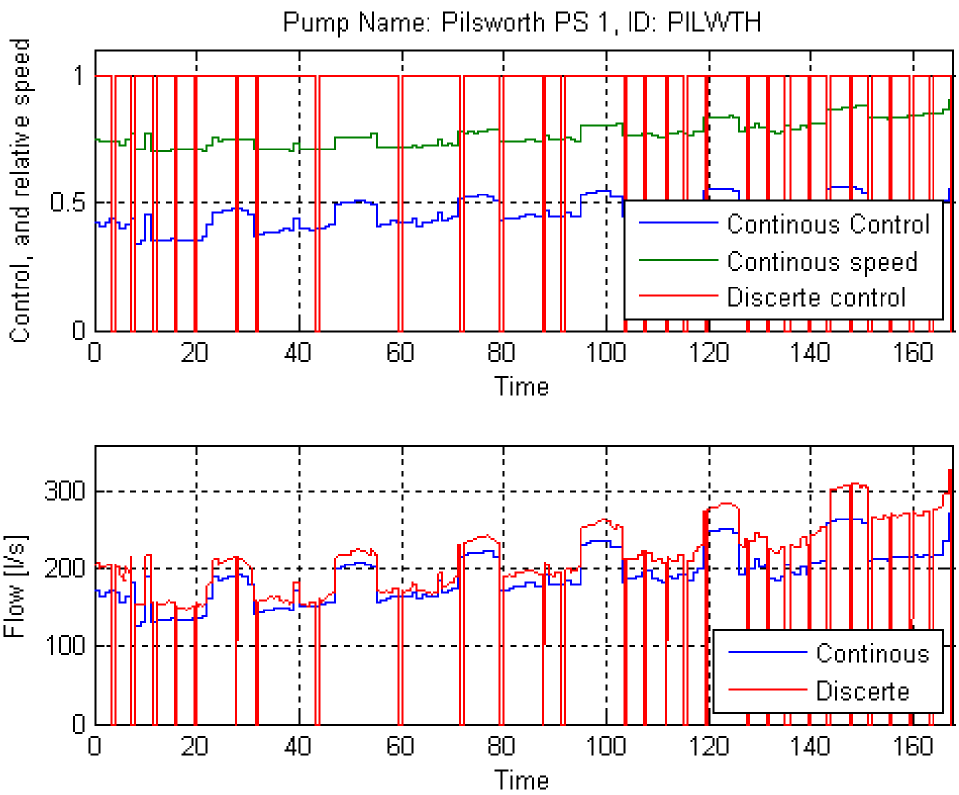


Figure 8.17 Continuous and discrete pump schedule for Pilsworth PS

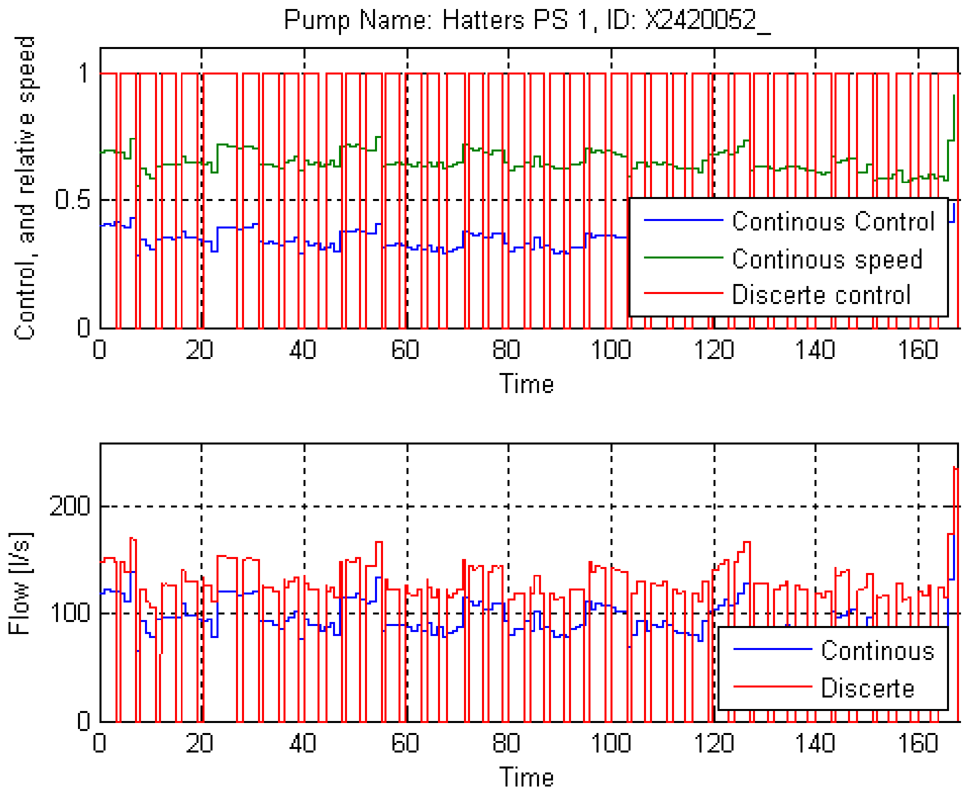


Figure 8.18 Continuous and discrete pump schedule for Hatters PS

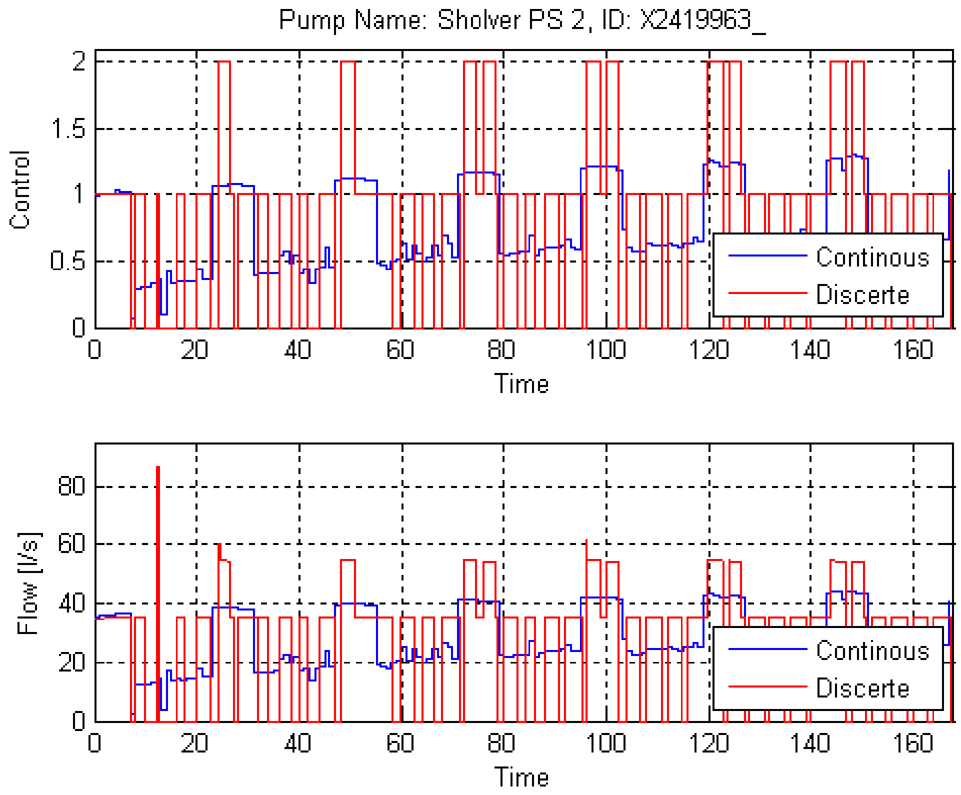


Figure 8.19 Continuous and discrete pump schedule for Sholver PS

8.6.3.2 Continuous and discrete reservoir trajectories

Figure 8.20 illustrate the reservoir trajectories for the optimal continuous and the discrete solutions of the pump schedule problem. The upper red and lower green straight lines represent the upper and lower reservoir bounds. Both trajectories show good matches as depicted in the figure which indicates that the continuous and discrete pumps flows are similar as suggested by equation(8.9).

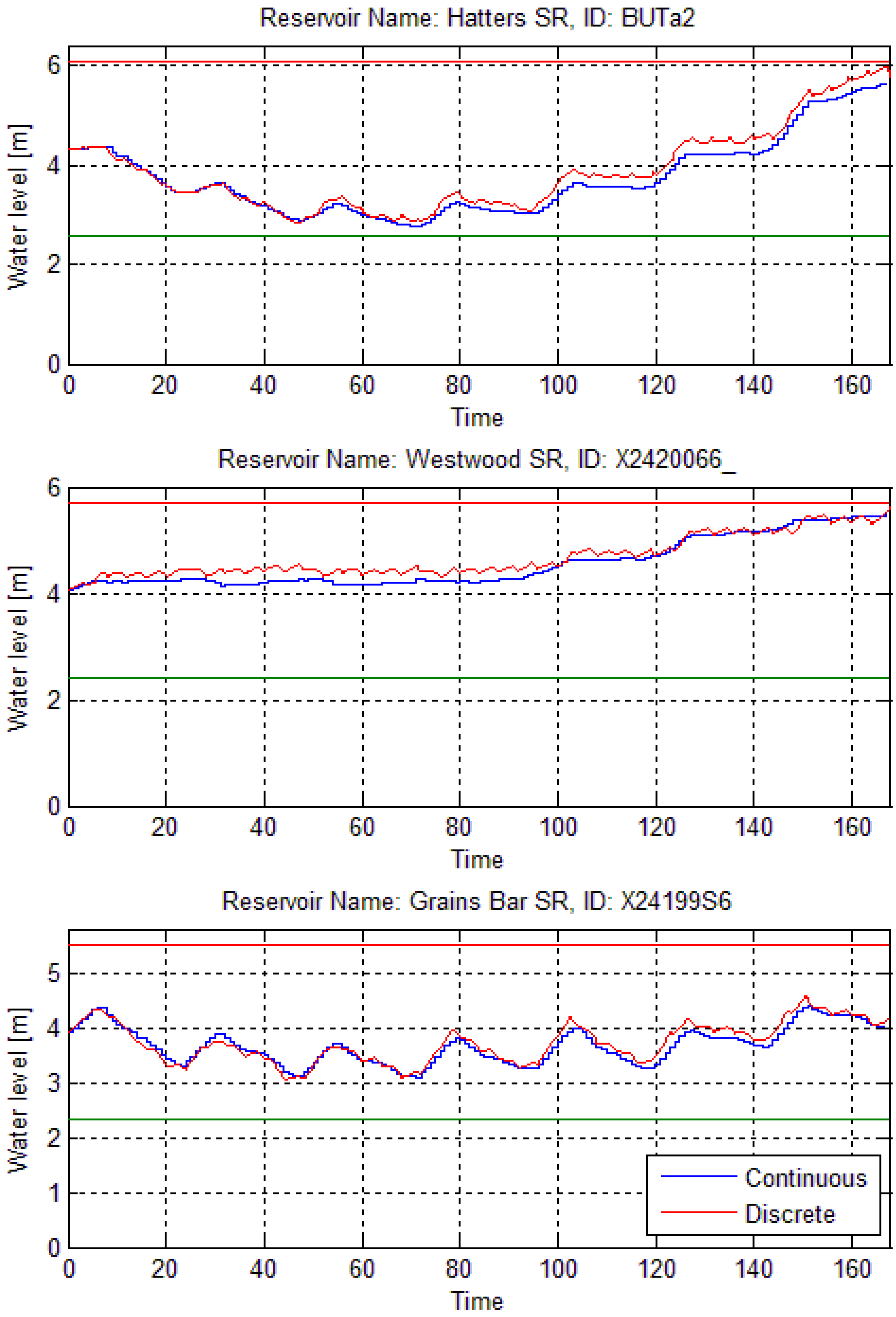


Figure 8.20 Continuous and discrete reservoir trajectories

8.6.3.3 Valves flow of continuous and discrete schedules

Figure 8.21 illustrates the continuous and discrete flows for the Chapel Rd and Sholver-Counthill valves. Both flows of Sholver-Counthill valve are identical, while discrete flow of Chapel Rd is lower than the continuous one in the periods of Newmarket Rd PS being "OFF".

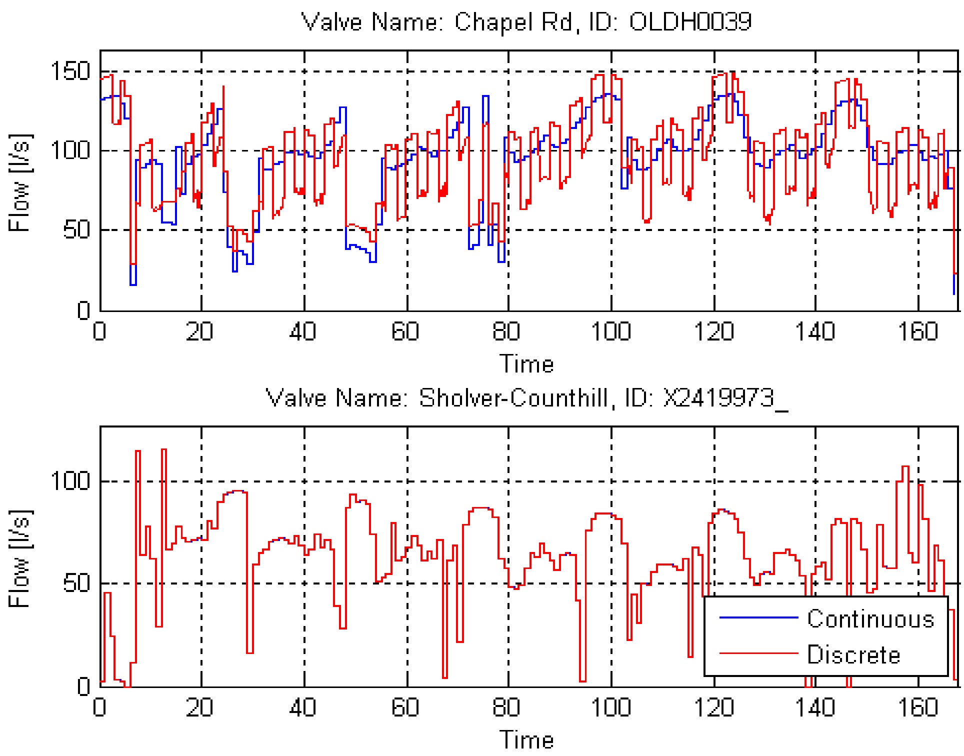


Figure 8.21 Valves flow of continuous and discrete schedules

8.6.3.4 Comparison of the current operation and the optimal schedule

Table 8.16 illustrates the final mass balance of each reservoir and the total final mass balance that are 11.4 Ml for current operation and 22.7 Ml for the optimal schedule. In this scenario, the total saving in pumping energy and cost are 30.8% and 34.9% respectively, as shown in Table 8.17.

Table 8.16 Reservoir mass balance [Ml]

Reservoir name	Current Operation	Optimal Schedule
Hartshead SR	-5.68	0.78
Hatters SR	5.03	5.40
Westwood SR	5.52	5.74
Werneth Park SR	1.57	2.47
Sholver SR	3.33	2.94
Readycon Dean SR	0.38	0.24
Grains Bar SR	-1.87	0.22
Counthill SR	3.05	3.05
Lowbrook SR	-1.08	0.02
Oldham Edge SR	1.10	1.92
Total	11.36	22.77

Table 8.17 Pumping Energy and cost

	Pumping Energy [KWhr]			**Pumping cost [£]**	
Pump name	**Current operations**	**Optimal Schedule**		**Current operations**	**Optimal Schedule**
Hatters PS 1	12112.93	4727.13		889.66	334.18
Hatters PS 2	0.00	0.00		0.00	0.00
Westwood PS 1	0.00	0.00		0.00	0.00
Westwood PS 2	1884.56	4675.96		134.57	290.10
Broadway PS	0.00	0.00		0.00	0.00
Werneth Park PS	6839.52	261.54		494.42	16.23
Grains Bar PS	0.00	0.00		0.00	0.00
Sholver PS 1	5025.14	1775.47		373.07	110.15
Sholver PS 2	5025.97	9033.04		373.13	646.11
Sholver PS 3	0.00	0.00		0.00	0.00
Wickenhall PS 1	0.00	0.00		0.00	0.00
Wickenhall PS 2	0.00	522.45		0.00	32.41
Bucktone Rd PS 1	0.00	0.00		0.00	0.00
Bucktone Rd PS 2	0.00	548.46		0.00	34.03
Lowbrook PS 1	2952.04	527.85		223.11	32.75
Lowbrook PS 2	0.00	0.00		0.00	0.00
Pilsworth PS 1	18062.71	10600.64		1329.53	757.64
Newmarket Rd PS	0.00	3228.96		0.00	230.23
Pilsworth PS 2	0.00	0.00		0.00	0.00
Total [KWhr]	51902.88	35901.51	**Total [£]**	3817.48	2483.82
saving [KWhr]		16001.37	**saving [£]**		1333.66
saving [%]		30.83	**saving [%]**		34.94

Taking into account only the costs associated with KWh usage of scheduled pumping stations and assuming summer tariff the optimised operation reduced the weekly electricity cost by 35% in comparison to the current operation (Computed from the provided Epanet model). In 7 day scenario "case 3" there is more chance to utilize the full reservoirs capacities over the optimization time horizon, hence more energy and cost savings are achieved in "case 3" than in the 24 hr scenario "case 2".

8.7 Summary

In this chapter a method was described for combined energy and pressure management via integration and coordination of pump scheduling with pressure control aspects. The method is based on formulating and solving an optimisation problem and involves utilisation of a hydraulic model of the network with pressure dependent leakage. The cost function of the optimisation problem represents the total cost of water treatment and pumping. Developed network scheduling algorithm consists of two stages. The first stage involves solving a continuous problem, where operation of each pump is described by continuous variables, and utilises the GAMS modelling language and the CONOPT3 non-linear programming solver. Subsequently, in the second stage continuous pump schedules are discretised using a heuristic algorithm.

Oldham water supply system managed by United Utilities (UU) has been provided as a case study. Network topology and current operation has been described, followed by description of the process of obtaining the network model for scheduling in Appendix B. The developed models full and simplified, showed good agreement with the reference Epanet model provided by UU. The network scheduling studies considered different reservoir constraints, and different initial reservoir levels. A comparison has been made between the cost of the current network operation and the optimised operation. The optimal schedule has reduced the KWh usage between 11 to 35% depending on the scenario.

8.7.1 Overview of optimisation results

The scenario optimised over 24hr horizon resulted in comparable savings around 58% when the flow from WTWs was optimised together with pump operation. It has been found that in these scenarios the bottom constraint was never hit for most reservoirs, due to the constraint on final reservoir level.

The third scenario "case 3" for one week horizon is the most relevant for two reasons:

- The optimiser could utilise full allowed capacity of the reservoirs and indeed the full range of constraints which are active for some reservoirs.

- Reservoir mass balance “the difference between the final total water volume in all reservoirs and the initial total water volume in all reservoirs”of optimised operation was larger than that of current operation by 10 Ml.

Note that in this scenario flows from WTW have not been optimised. It has been demonstrated during solving other scenarios that optimisation of flow from WTWs considerably increases the savings.

For all scenarios not only the cost, but also the actual use of electrical energy was significantly reduced, since the tariffs were nearly flat. Furthermore, optimised operation resulted in savings in leakage between 2% and 4% depending on the scenario. Note that in the considered scenarios the cost of electrical energy is high compared to the leakage level, therefore reducing the energy cost was of higher importance during the optimisation process, compared to reducing the leakage.

The savings are due to operating the network optimally, or close to being optimal. From hydraulic point of view, when compared to the current operation, the savings come mainly from:

- Running pumps at lower speed, which is more efficient for the considered WDS.
- Pumping more intensively during cheap tariff period.
- Use of pumps that are not used in current operation. Due to this the flow from Aqueduct is split into two paths, which results in decreased head drop, hence less energy is wasted.
- Optimised flow from sources. In scenarios where the sources were optimised the savings were significantly increased compared to corresponding scenarios without sources optimisation.

Three scenarios with different lower reservoirs constraints (LRC) and the same initial reservoirs level have been solved to study the effect of changing LRC on the continuous solution and presented in “Appendix C”. The results showed that, changing the lower reservoirs constraints have a minor impact on the continuous solution of the optimization problem. Only the Pilsworth PS and Hatters PS flows have slightly changed which affected the trajectory of Hatters reservoir. And there is no expected saving in both pumping energy and cost in the discrete solution.

By reviewing and analysing the 7 days optimal schedules results, it has been noticed that the pumps flows and the reservoirs trajectories take a cyclic patterns especially after the second day due to the effect of initial reservoir levels are vanishing.

Chapter 9

9 Feedback Rules for Operation of Pumps in a Water Supply System

In this chapter, a novel approach of optimising the operation of pump stations in WDSs based on optimal feedback rules has been investigated. Operating and controlling the pump stations via optimal feedback rules aims to minimize the energy consumptions, and provides a robust control policy. The optimal feedback rules have been derived using Genetic Algorithm (GA).

9.1 Introduction

Typically the real time control for time varying tariffs is implemented in a predictive control fashion, in which an optimal time schedule is calculated ahead over 24 hours period by a solver and recalculated at regular intervals e.g. 1 hour. In order to operate the scheme in real time the solver must be sufficiently fast and this may not always be possible for big water supply systems. In this chapter, a method to synthesize feedback control rules is proposed taking into account a time varying tariff. The rules are calculated off-line and then can be implemented in local PLCs or in a control room. Once the rules are implemented the response to the changing state of the water system is instantaneous.

The feedback rules have been determined by a GA. Each pump station has a rule described by two water levels in a downstream reservoir and a value of pump speed for each tariff period. The lower and upper water levels of the downstream reservoir correspond to the pump being ON or OFF. The approach has been applied to a large scale water supply system and compared with the traditional time schedule approach developed in chapter 8. The achieved cost for the feedback control is only slightly higher than that for the time schedule approach. However, the feedback control by its nature is more robust and performs well in the presence of uncertainty in water demands and in inaccuracy of hydraulic models.

9.2 Problem Outline

The optimisation problem of the optimal feedback rules for pump stations in WDSs calculates the least operational cost for pump operations and treatment works for a given period of time. In this study, the operational cost includes only the pumping energy cost over 1 week of operation. The decision variables for each pump stations are switching levels (defined by two water levels in the downstream reservoir of the pump station) and a pump speed for each tariff period, but WTW outputs can be considered for further investigations. The problem has the following three elements:

- hydraulic model of the network
- fitness function
- decision variables
- constraints

The scheduling problem is succinctly expressed as: minimise pumping cost, subject to the network equations and operational constraints. The three elements of the problem are discussed in the following subsections.

9.2.1 Hydraulic model

Each network component has a hydraulic equation. The fundamental requirement in the optimisation problem is that all calculated variables satisfy the hydraulic model equations. The network equations are non-linear and represents the equality constraints in the optimisation problem. The network equations used to describe component hydraulics, energy conservation and mass balance are those described in chapter 3 (section 3.4). In the current study, Epanet (Rossman 2000) has been employed as a network hydraulic simulator, and has been linked to Matlab GA toolbox (Chipperfield and Fleming 1995; MathWorks 2010).

9.2.2 Fitness function

The fitness function to be minimised is the total specific pumping energy cost (energy cost per 1 Ml of pumped water) that depends on the efficiency of the pumps and the electricity tariff. The tariff is a function of time with cheaper and more expensive periods. The objective function considered over a given time horizon [k_0, k_f] is given by equation(9.1):

$$\phi = \frac{\sum_{j \in J_p} \sum_{k=k_0}^{k_f} \gamma_p^j(k)\, f_j\left(q^j(k), u^j(k), s^j(k)\right)}{\sum_{j \in J_p} \sum_{k=k_0}^{k_f} q^j(k)} + \sum_{k=k_0}^{k_f} \Theta(k) \tag{9.1}$$

where J_p is the set of indices for pump stations. $u^j(k)$ is a number of pumps being "ON". $s^j(k)$ is a pump speed (for variable speed pumps). The function $\gamma_p^j(k)$ represents the electrical tariff. The term $f_j\left(q^j(k), u^j(k), s^j(k)\right)$ represents the electrical power consumed by pump station j. Θ is a penalty value added to the fitness function if the constraints are violated, or if the generated solution (chromosome) is not feasible, and is estimated as shown in equation (9.3). The mechanical power is obtained by multiplying the flow $q^j(k)$ and the head increase $\Delta h^j(k)$ across the pump station. The head increase $\Delta h^j(k)$ can be expressed in terms of flow in the pump hydraulic equation, so that the cost term depends on the pump station flow $q^j(k)$ and pump speed and number of pumps being "ON". Electrical power consumed by the pump can be calculated from mechanical power using either the pump efficiency or pump power characteristics. In this work pump power characteristics were used and electrical power consumed by the pump station was calculated by adapting the formula, taken from (Ulanicki et al. 2008b), given as follows:

$$P(q,u,s) = \begin{cases} us^3\left(E\left(\dfrac{q}{us}\right)^3 + F\left(\dfrac{q}{us}\right)^2 + G\dfrac{q}{us} + H\right) & \text{if} \quad u,s > 0, \\ 0 & \text{otherwise} \end{cases} \tag{9.2}$$

where E, F, G, H are constants of power coefficients for a given pump. Note that, for simplicity of notation in equation (9.2) the time-indices k and superscripts j for terms q, u, s were omitted.

$$\Theta(k)=\begin{cases} 1000.0\times\left(t_f-t_u\right) & \text{if} \quad \text{infeasible or unbalanced simulation} \\ +\left(1000\times\sum_{i\in N_{node}}\left(p_{\min}-p_i\left(k\right)\right) \qquad \text{if} \qquad p_i\left(k\right)<p_{\min}\right) \\ +\left(1000.0\times\sum_{i\in N_{SR}}\left(h_{f,i}^{\min}-h_f\left(k\right)\right) \qquad \text{if} \qquad h_f\left(k\right)<h_{f,i}^{\min}\right) \\ +\left(1000.0\times\sum_{i\in N_{SR}}\left(h_f\left(k\right)-h_{f,i}^{\max}\right) \qquad \text{if} \qquad h_f\left(k\right)>h_{f,i}^{\max}\right) \\ +\left(1000.0\times\left(\Phi\left(k_0\right)-\Phi\left(k_f\right)\right) \qquad \text{if} \quad \Phi\left(k_f\right)<\Phi\left(k_0\right)\right) \end{cases} \tag{9.3}$$

Where t_f is the entire simulation time horizon. t_u is the time at which the simulation is corrupted due to infeasible rules. h_f , $h_{f,i}^{\min}$ and $h_{f,i}^{\max}$ are water level, the lower and the upper bounds of water level in reservoir i which belongs to the set of reservoir N_{SR}. p_i and p_{min} are the pressure and minimum allowed pressure at node i belongs to the set of node N_{node}. $\Phi\left(k_0\right)$ and $\Phi\left(k_f\right)$ are the initial and final total water volume in all reservoirs.

9.2.3 Inequality constraints and penalties

In addition to equality constraints described by the hydraulic model equations, operational constraints have been applied to keep the system-state within its feasible range. The typical requirements of network scheduling are concerned with reservoir levels in order to prevent emptying or overflowing, and to maintain adequate storage for emergency purposes:

$$h_f^{\min}\left(k\right)\le h_f\left(k\right)\le h_f^{\max}\left(k\right) \quad \text{for} \quad k\in\left\langle k_0,k_f\right\rangle$$

where $h_f(k)$ is the reservoir water level at time k. $h_f^{\min}$ and $h_f^{\max}$ are the lower and upper bounds of the reservoir constraints. Similar constraints can be applied to the heads at critical nodes in order to maintain required pressures throughout the water network. Other important constraints are on the final water level of reservoirs and the final mass balance in all reservoirs, such that the final water level in any reservoir is greater than or equal to the initial reservoir level.

$$h_f\left(k_0\right)\ge h_f\left(k_f\right)$$

and the final total mass balance (total final water volume of all reservoirs), Φ, is greater than or equal to the initial volume:

$$\Phi\left(k_f\right) \geq \Phi\left(k_0\right)$$

without these constraints least-cost optimisation would result in emptying all reservoirs. If the system violates any of the above stated constraints, a penalty value, Θ is added to the fitness function, equation(9.1).

9.3 Decision Variables

The optimal feedback rule for each pump station is described by two water levels in a downstream reservoir and a value of pump speed for each tariff period. For fixed speed pump, the feedback rules are described by two water levels in the downstream reservoir only. The lower and upper water levels of the downstream reservoir correspond to the pump being ON or OFF.

Using switching levels to control the fixed speed pump may result in inefficient operations because it does not consider tariff periods, therefore, it is recommended for further investigation to use different switching levels for different tariff periods. However, as a first attempt in this research, switching level for each pump is not time dependent.

9.4 GA Implementation

The described optimal algorithm has been coded in Matlab, using the provided GA toolbox linked to Epanet 2 as hydraulic simulator. The algorithm can be used for design stage and off-line planning studies such as assessing the benefits of introducing the optimal feedback control or for online operation, which may be implemented in feedback control as a real time control scheme. Figure 9.1 illustrates how the fitness function is calculated using Epanet.

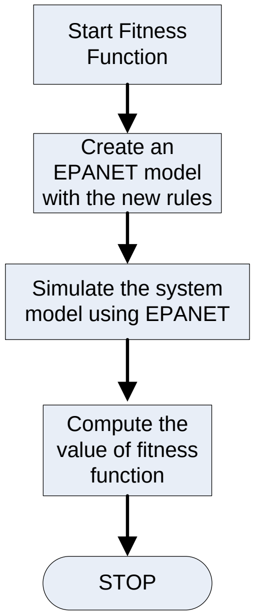


Figure 9.1 Flowchart of GA and fitness function

In the following section, a case study has been solved to assess the performance of the developed strategy. The results of the optimal feedback rules for pump operation determined by GA have been compared with the solution of the optimal time schedule obtained by NLP method described in Chapter 8.

9.5 Case Study

The approach has been applied to a large-scale water supply system of Oldham area which is discussed in chapter 8 and more details are presented in "Appendix B", and compared with the traditional time schedule approach that was developed in chapter 8. Table 9.1 shows the types of pump stations, the corresponding reservoirs, and the number of decision variable of each pump station.

The optimal feedback rules and the optimal traditional time schedule are computed for all pump stations except Broadway PS and Grains Bar PS. Broadway PS is out of service, and Grains Bar PS is a booster pump, which deliver the predefined required demand. The hydraulic Epanet and Finesse models, GAMS code and CONOPT output result file of this case study are provided in the enclosed CD, file descriptions, paths and locations are listed in Appendix D.

Table 9.1. Pump stations, corresponding downstream reservoir, and the number of decision variable

Pump Station	Type of drive*	Controlled by reservoir level	Optimized	Number of decision variables
Pilsworth PS	VSD	Hatters SR	Yes	4
Broadway PS	FSD	Werneth Park SR	No	
Newmarket Rd PS	VSD	Werneth Park SR and Hartshead SR	Yes	6
Hatters PS	VSD	Westwood SR	Yes	4
Westwood PS	VSD	Oldham Edge SR	Yes	4
Werneth Park PS	VSD	Lowbrook SR	Yes	4
Lowbrook PS	FSD	Counthill SR	Yes	2
Buckstones Road PS	FSD	Sholver Sr	Yes	2
Sholver PS	FSD	Grains Bar Sr	Yes	2
Grains Bar PS	VSD	booster	No	
Wickenhall PS	FSD	Readycon Dean Sr	Yes	2

* *FSD stand for fixed speed drive, VSD stand for variable speed drive.*

9.5.1 Results and Discussion

The GA was allowed 51 generations to reach the optimal feedback rules to control the operation of the pump stations, each generation contained 300 chromosomes (populations size) with 20% migration fraction.

Figure 9.2 depicts the progress of GA in terms of the best and mean values of the fitness function of the population at every generation. The derived feedback rule for each chromosome is simulated using Epanet software over 7 day of real demand data.

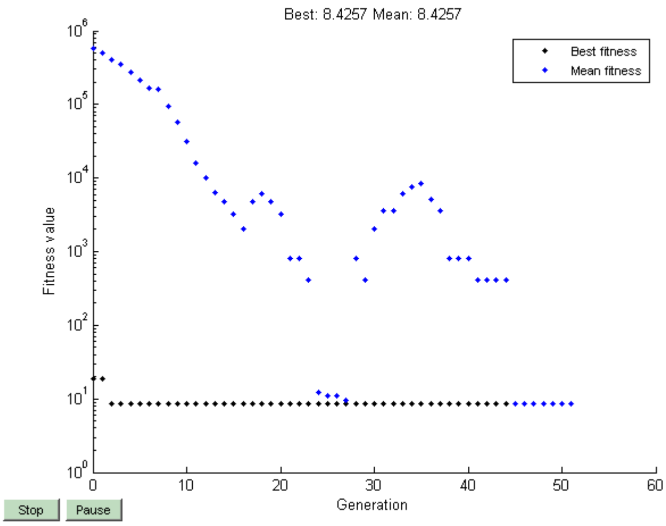


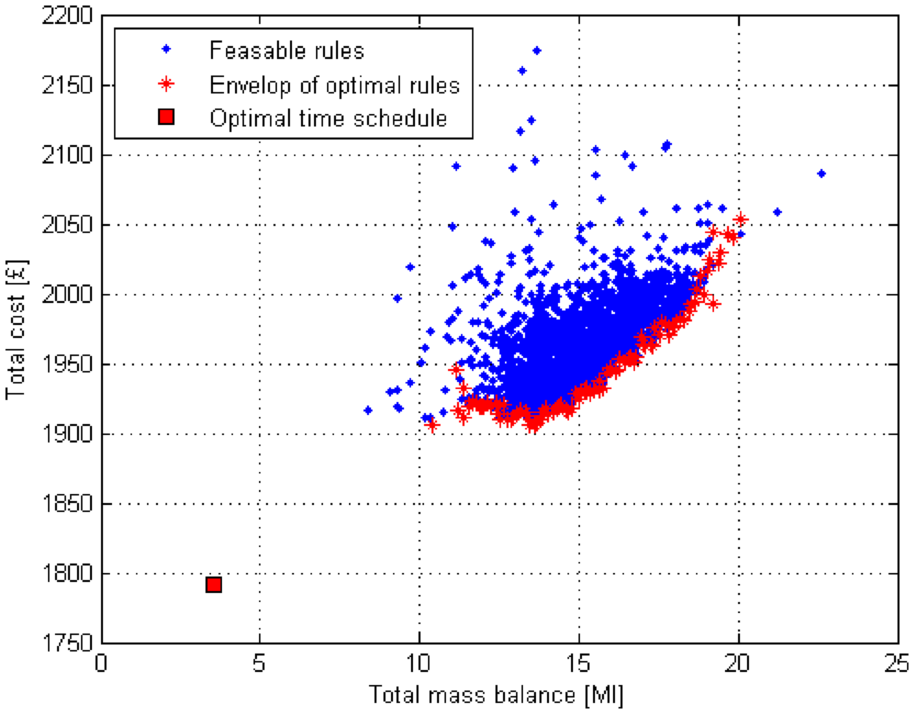
Figure 9.2 Solution progress of GA

Table 9.2 shows the lower and upper reservoir switching levels for each pump, that are used to switch the pump ON and OFF. It also shows the relative pump speed for variable speed pumps in the cheap and expensive tariff periods.

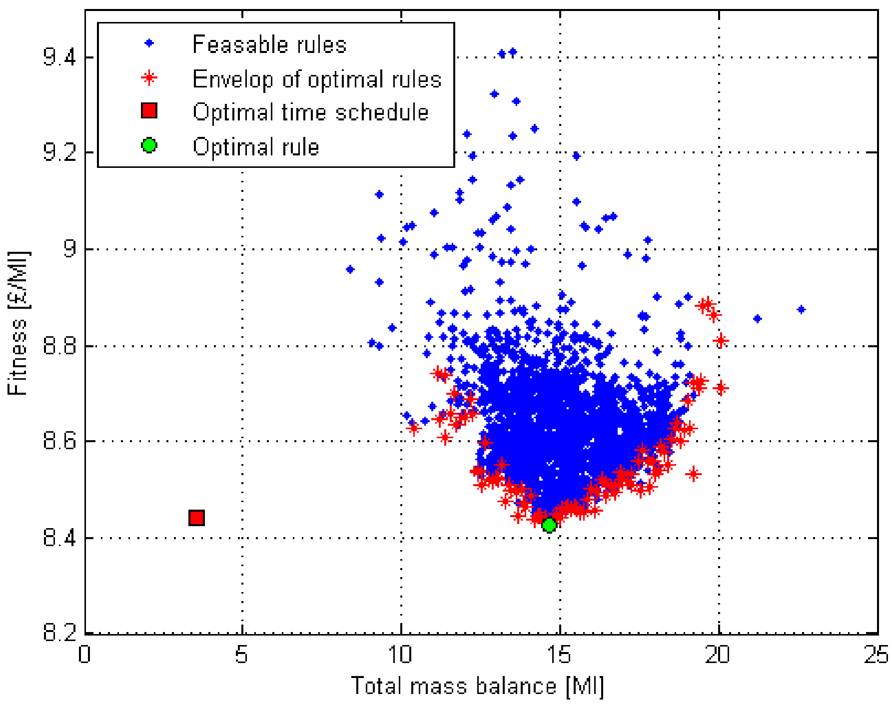
Table 9.2 The optimal rule for pump operation derived over 1 week

<table>
<tr><th rowspan="2">Pump Station</th><th rowspan="2">Type of drive</th><th rowspan="2">Controlled by reservoir</th><th rowspan="2">Lower SR level % (ON)</th><th rowspan="2">Upper SR level % (OFF)</th><th colspan="2">Relative speed in tariff period</th></tr>
<tr><th>cheap</th><th>expensive</th></tr>
<tr><td>Pilsworth PS</td><td>VSD</td><td>Hatters SR</td><td>86</td><td>91</td><td>77%</td><td>70%</td></tr>
<tr><td rowspan="2">Newmarket Rd PS</td><td rowspan="2">VSD</td><td>Werneth Park SR</td><td>82</td><td>89</td><td rowspan="2">75%</td><td rowspan="2">71%</td></tr>
<tr><td>Hartshead SR</td><td>71</td><td>81</td></tr>
<tr><td>Hatters PS</td><td>VSD</td><td>Westwood SR</td><td>62</td><td>93</td><td>67%</td><td>58%</td></tr>
<tr><td>Westwood PS</td><td>VSD</td><td>Oldham Edge SR</td><td>44</td><td>87</td><td>84%</td><td>73%</td></tr>
<tr><td>Werneth Park PS</td><td>VSD</td><td>Lowbrook SR</td><td>---</td><td>---</td><td>---</td><td>---</td></tr>
<tr><td>Lowbrook PS</td><td>FSD</td><td>Counthill SR</td><td>59</td><td>83</td><td rowspan="4">NA</td><td rowspan="4">NA</td></tr>
<tr><td>Buckstones Road PS</td><td>FSD</td><td>Sholver SR</td><td>46</td><td>66</td></tr>
<tr><td>Sholver PS</td><td>FSD</td><td>Grains Bar SR</td><td>50</td><td>88</td></tr>
<tr><td>Wickenhall PS</td><td>FSD</td><td>Readycon Dean SR</td><td>45</td><td>75</td></tr>
</table>

Figure 9.3 (a) shows the total pumping cost in [£] on the vertical axis for all derived feasible rules by GA and for the optimal time schedule, and the final total mass balance in all reservoir in [Ml] on the horizontal axis. Each point represents the total pumping cost and the final mass balance of all reservoirs for one set of feasible rules. The scatter of lowest cost for each mass balance forms a Pareto line for the optimal derived rules in terms of the total pumping cost. The Pareto line of the total cost has a convex shape of minimum cost of £1906 at a mass balance of 13.6 Ml and a fitness function of 8.49 £/Ml. This minimum does not represent the optimal operation condition because the mass balance itself has an effect on the total cost, and can be used as a contribution factor to evaluate the fitness function. For this reason, anther representation of the fitness function has been chosen to evaluate the efficiency of the pumping system. Figure 9.3 (b) shows the final total mass balance for all reservoirs in [Ml] on the horizontal axis and the fitness function in [£/Ml] on the vertical axis. The fitness function is defined as the total pumping cost in [£] divided by the total pumped water in [Ml] or the specific pumping cost. Again, the minimum fitness function forms a Pareto line, which has convex shape and has a minimum of 8.43 £/Ml at mass balance of 14.68 Ml and a total pumping cost of £1916.



(a)



(b)

Figure 9.3 (a) Total cost and (b) the fitness value of the feasible derived rule by GA

The described NLP algorithm in Chapter 8, has also been applied to the same case study to find the optimal time schedule for pump operation. The results of optimal feedback rules and optimal time schedule are discussed and compared below.

9.5.2 Pump flows and efficiencies

The data of pump operation in terms of total delivered flow, pumping energy and total pumping cost are presented in Table 9.3 for the optimal feedback rules and the optimal time schedules. The total delivered flow for the optimal feedback rules is 15 Ml higher than for the optimal time schedules and this explains the differences in the total pumping energy and cost. The achieved cost for the feedback control is higher than that for the time schedule approach, but both have similar energy cost per 1 Ml of pumped water (specific energy cost).

Table 9.3 the data of pump operation

	Delivered Flow [Ml]		Energy consumption [KWhr]		Energy cost [£]	
Pump name	**Optimal feedback rules**	**Optimal time schedule**	**Optimal feedback rules**	**Optimal time schedule**	**Optimal feedback rules**	**Optimal time schedule**
Pilsworth PS	114.59	108.39	9340.08	8930.96	665.10	638.39
Newmarket Rd PS	10.34	4.41	2145.51	783.94	144.62	52.47
Hatters PS	57.38	55.23	3224.92	4073.26	228.89	289.17
Westwood PS	16.15	15.68	3936.57	3539.84	273.15	219.61
Werneth Park PS	0.00	0.00	0.00	0.00	0.00	0.00
Lowbrook PS	9.83	9.74	1955.42	1935.13	132.44	121.07
Buckstones Road PS	0.00	0.00	0.00	0.00	0.00	0.00
Sholver PS.1	17.16	1.43	5737.58	582.46	414.92	36.14
Sholver PS.2	0.00	15.36	0.00	5324.66	0.00	377.69
Wickenhall PS	1.89	1.91	799.62	858.38	56.47	56.60
Total	227.35	212.15	27139.69	26028.63	1915.59	1791.14
Total divided by total flow			119.37 [kWhr/Ml]	122.69 [kWhr/Ml]	8.43 [£/Ml]	8.44[£/Ml]

The delivered flow and the efficiencies of pump stations Pilsworth PS, Hatters PS and Sholver PS are presented in Figure 9.4(a-c) and Figure 9.5 (a-c), respectively. There is a heavy pumping during the cheap tariff for both approaches achieved with high speed of variable speed pump. The optimal feedback rules has advantage of small number of switching, which increase the pump stations life span and reduce the maintenance cost.

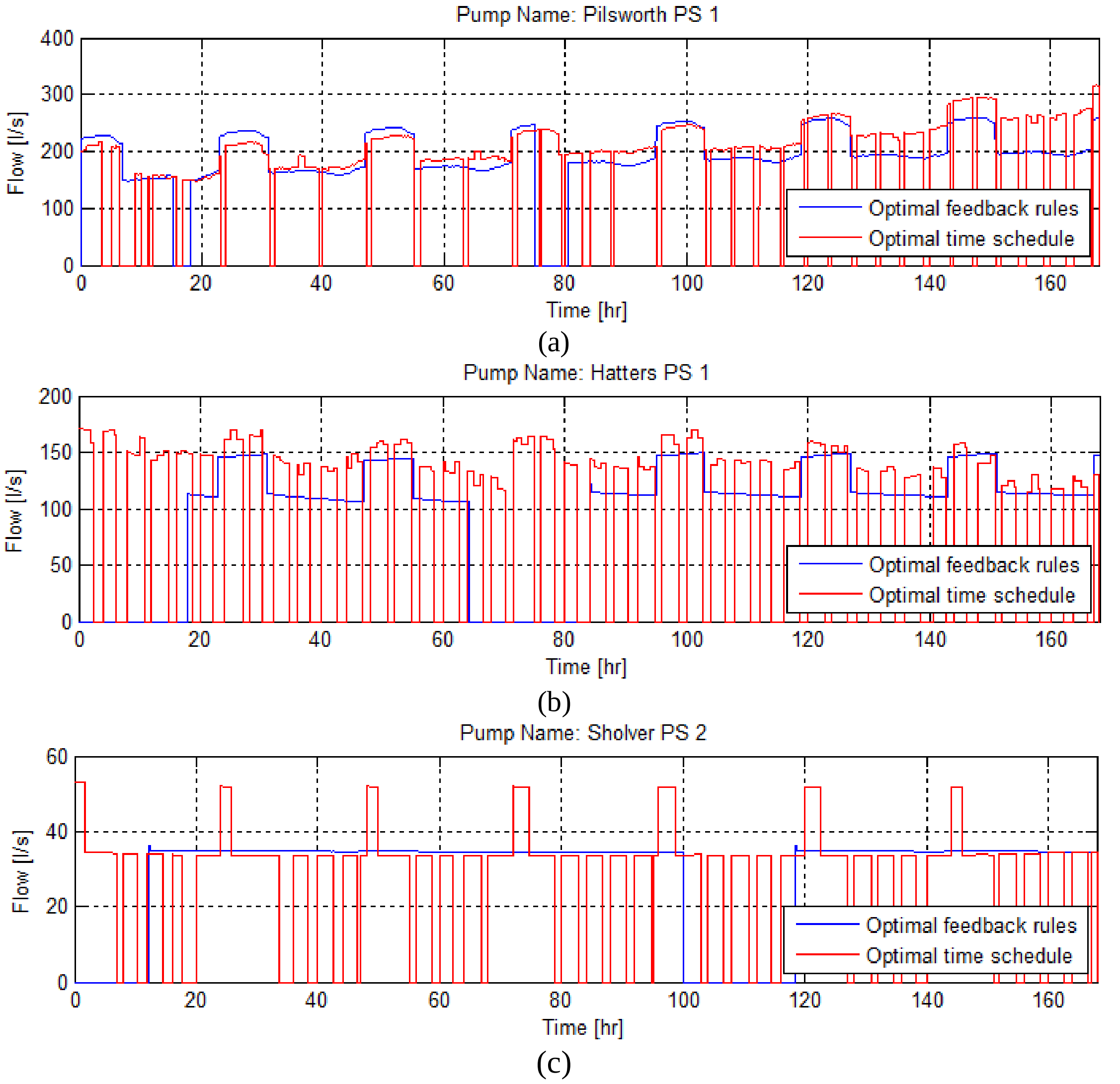


Figure 9.4 Pump flows for optimal feedback rules and optimal time schedules for Pilsworth PS, Hatters PS and Sholver PS.

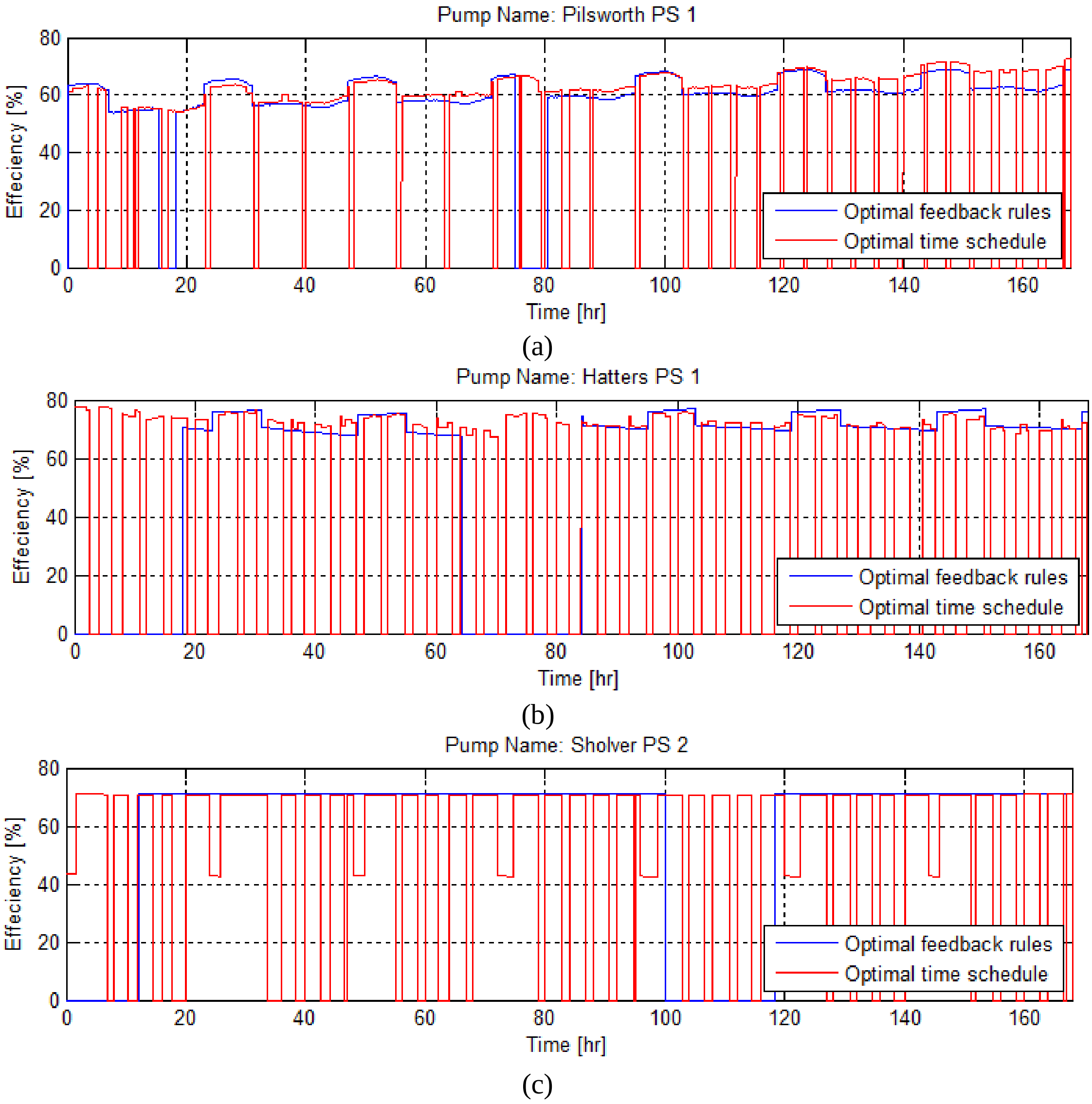


Figure 9.5 Pumps efficiencies for optimal feedback rules and optimal time schedule for Pilsworth PS, Hatters PS and Sholver PS.

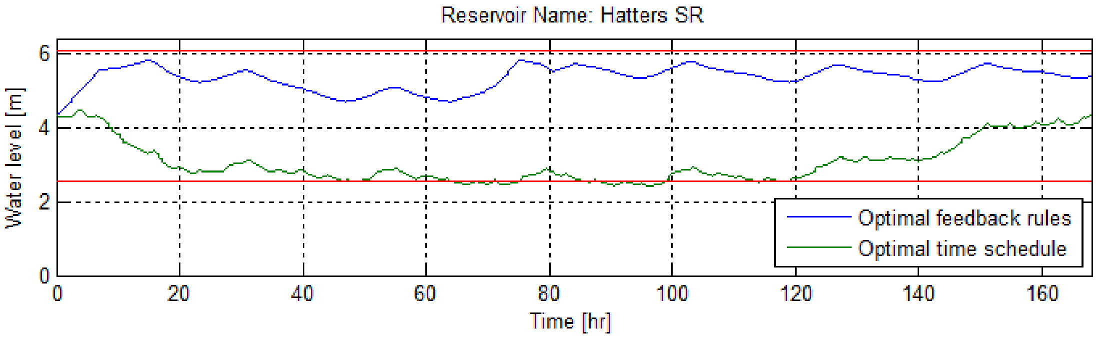
9.5.3 Reservoir trajectories and mass balance

Table 9.4 summarises the final mass balance for each reservoir in the system and the total mass balance of all in [Ml]. For optimal time schedule, the total mass balance is 3.56 ML, while for the optimal feedback rules the total mass balance is 14.68 Ml.

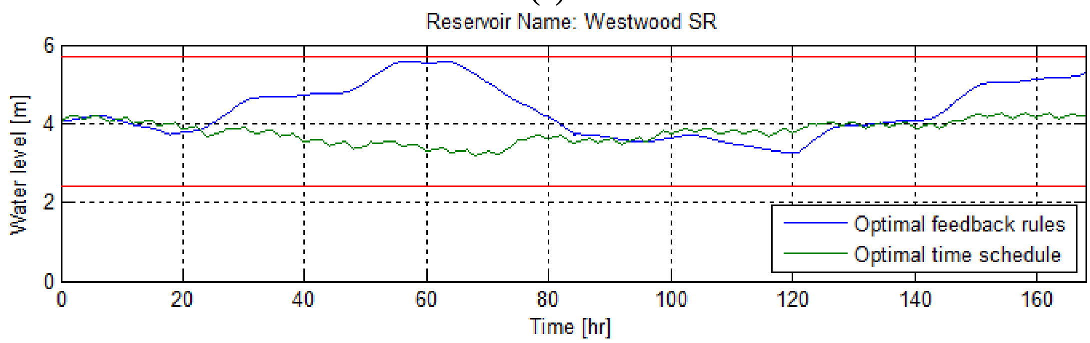
Table 9.4 Reservoir mass balance [Ml]

Reservoir name	Optimal feedback rules	Optimal time schedule
Hartshead SR	1.40	0.03
Hatters SR	4.02	0.29
Westwood SR	4.44	0.50
Werneth Park SR	2.04	0.21
Sholver SR	-0.47	-0.37
Readycon Dean SR	-0.04	0.00
Grains Bar SR	0.32	-0.01
Counthill SR	-0.53	-0.06
Lowbrook SR	2.84	2.80
Oldham Edge SR	0.66	0.16
Total [Ml]	14.68	3.56

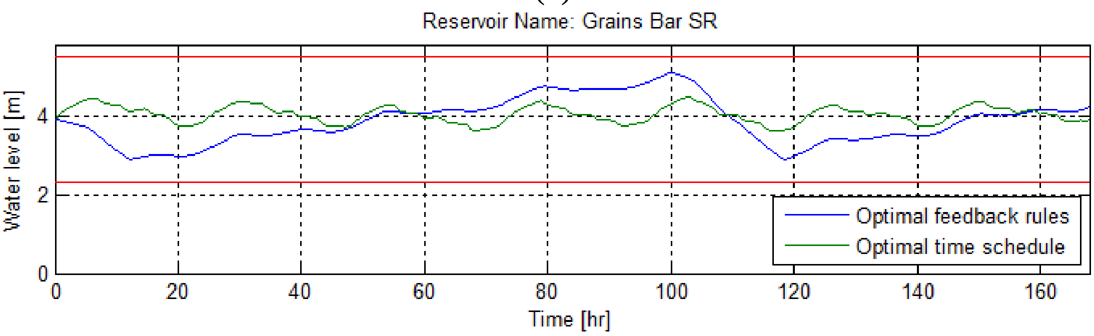
Figure 9.6 (a-s) illustrates the water levels in the reservoirs Hatters SR, Westwood SR and Grains Bar SR on the vertical axis for both optimal feedback rules and the optimal time schedule, over 1 week with 1 hour step. The minimum and maximum bounds on the water level in each reservoir are represented by the red lines.



(a)



(b)



(c)

Figure 9.6 Reservoirs trajectories for Hatters SR, Westwood SR and Grains Bar SR.

9.5.4 Sensitivity of feedback rules to the demand and initial reservoirs levels

A sensitivity studies of the derived optimal feedback control rules to the demand levels and the initial reservoir levels have been conducted. The sensitivity to the demand levels has been established by simulating the hydraulic model at different demand levels from 85% to 115% of the original demand (the demand level used to drive the optimal feedback rules) with 5% increment for each run. The source flows have not been optimized in the current study, the source flows have been incremented by the same level to cope with the change in the demand. Figure 9.7 depicts the effect of demand levels on the total pumping cost, specific cost, pumped flow and final reservoirs mass balance. As shown in the figure, the system can be operated in an optimal or near optimal condition if the demand level changes between 95% and 105% of the original demand. If the demand level is lower than 95% of the original demand, the specific operating cost increases slightly, but higher increase in the specific cost is observed when the demand increases above 105% of the original. Due to this finding, the optimal feedback rules should be derived seasonally to cope with the changing demand, and to operate the system optimally around the year.

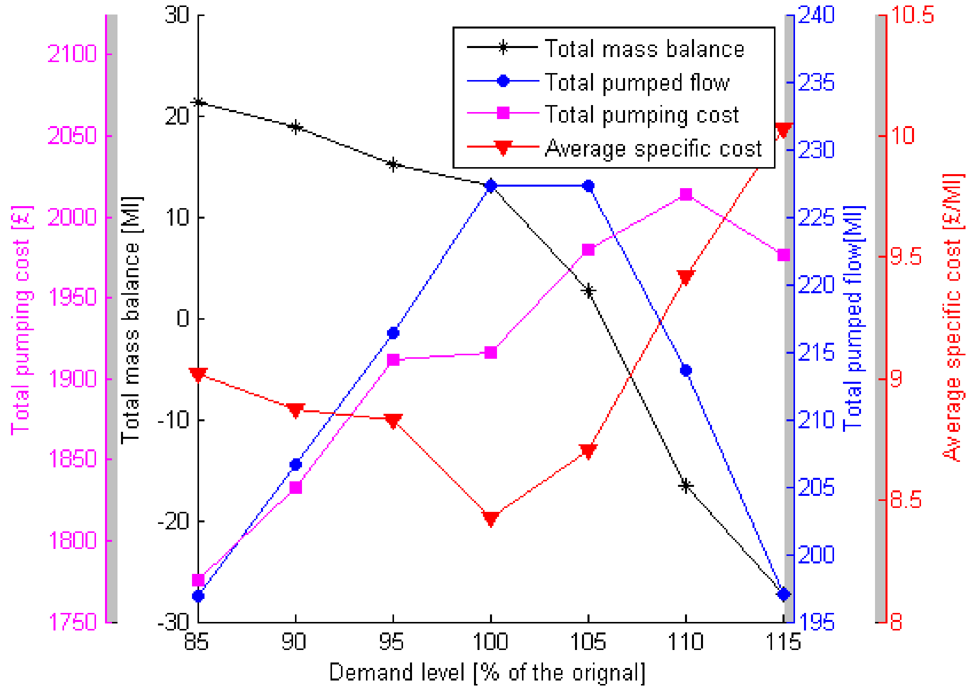


Figure 9.7 The sensitivity of optimal feedback rules to demand levels

The sensitivity to the initial reservoirs levels is established by the same method by simulating different initial levels varying from 40% to 90% of the full reservoir range with 10% increments. Figure 9.8 illustrates the sensitivity of the feedback rules to the initial reservoirs levels. As shown in the figure, total pumping cost, specific cost, pumped flow and final reservoirs mass balance decrease as the initial reservoirs levels increase. This behaviour is expected due to the utilization of the existing volume of water stored initially in the reservoirs.

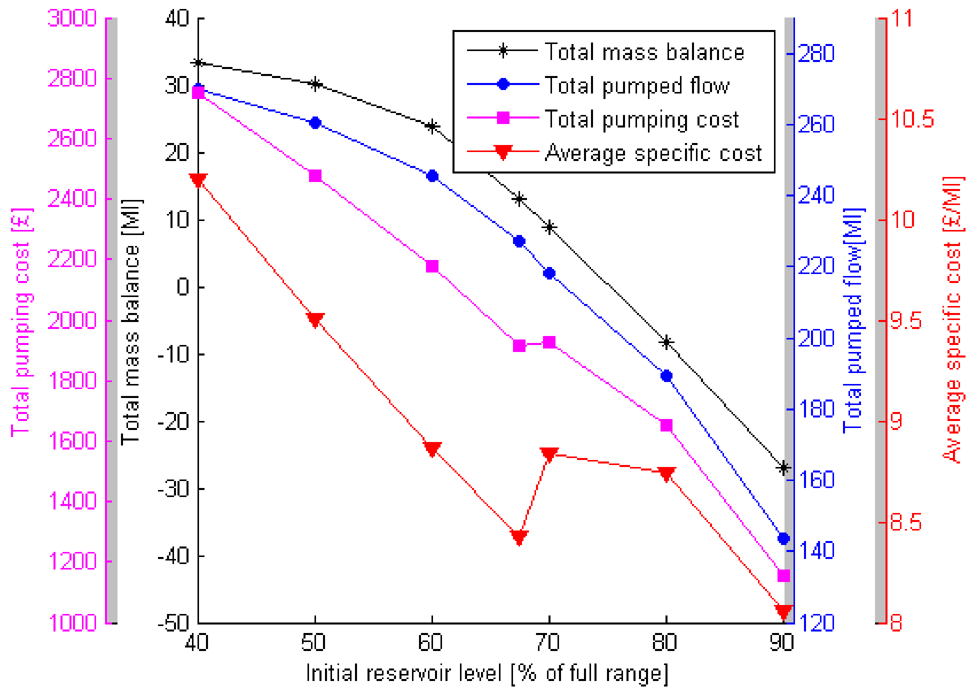


Figure 9.8 The sensitivity of optimal feedback rules to initial reservoirs levels

Further investigations on the effect the simulation time horizon have been conducted. The optimal feedback rules have been derived over a simulation time horizon of 4 weeks. In comparison with the optimal rules derived over 1 week, the fitness value of the derived optimal rules has been slightly changed to 8.3 £/Ml with total mass balance of 6.2 Ml, while the switching levels and pump speeds have significant changes as shown in Table 9.5.

Table 9.5 The optimal rule for pump operation derived over 4 weeks

Pump Station	Type of drive	Controlled by reservoir	Lower SR level % (ON)	Upper SR level % (OFF)	Relative speed in tariff period	
					cheap	expensive
Pilsworth PS	VSD	Hatters SR	73	85	68	70
Newmarket Rd PS	VSD	Werneth Park SR	63	72	62	63
		Hartshead SR	61	80		
Hatters PS	VSD	Westwood SR	64	78	58	66
Westwood PS	VSD	Oldham Edge SR	54	76	78	82
Werneth Park PS	VSD	Lowbrook SR	48	91	75	94
Lowbrook PS	FSD	Counthill SR	71	91	NA	NA
Buckstones Road PS	FSD	Sholver SR	59	78		
Sholver PS	FSD	Grains Bar SR	68	85		
Wickenhall PS	FSD	Readycon Dean SR	55	80		

9.6 Summary

The optimal feedback rules have been derived by a GA to control the operation of pump stations. Each pump station has a rule described by two water levels in a downstream reservoir and a value of pump speed for each tariff period. The lower and upper water levels of the downstream reservoir correspond to the pump being ON or OFF. The approach has been applied to a large scale water supply system and compared with the traditional time schedule approach. For both results of optimal feedback rules and optimal time schedule, the system is pumping more water in the cheap tariff cost by increasing the speed of variable speed pumps. The achieved cost for the feedback control is slightly higher than that for the time schedule approach but both have a similar energy cost per 1 Ml of pumped water. The feedback control by its nature is more robust and performs well in the presence of uncertainty in water demands and in inaccuracy of hydraulic models. In the considered case study, the optimal feedback rules had advantage of long time of continuous operation of the pumps and the smaller number of switching, which increase the pump stations life time and reduce the maintenance cost as well.

For Oldham case study, a sensitivity studies of the derived optimal feedback control rules to the demand levels, the initial reservoir levels and the simulation time horizon have been conducted, and the results showed that the derived rules can operate the system near optimum for the demand varying between 95% and 105% of the original demand. Due to this finding, the optimal feedback rules should be derived seasonally to cope with the demand changes. Changes of the initial reservoirs levels do not show any undesired effect, because the rules are calculated using 7 day horizon removing the effect of the initial reservoirs levels on the obtained results. A quite similar fitness values have been obtained by derived the rules over 1 week and 4 weeks as a simulation time horizon, but with significant changes in the switching levels and pump speeds. Due this finding, it is recommended to drive the optimal feedback rules using long simulation time horizon.

Chapter 10

10 Conclusion and Future Work

Water demands are increasing while the recourses are diminishing therefore the leakage reduction in WDSs has become an important objective for the water industry.

The benefits of applying pressure control policy in WDS in order to reduce the leakage have been discussed. A fast and efficient method to calculate the optimal time schedules and flow modulation curves for the boundary and internal PRVs has been presented in order to minimise the leakage in WDSs. The cost of boundary flows which include leakage flows is minimised. The boundary and internal PRVs have been treated differently, the decision variable for a boundary valve is PRV set-point whereas for the internal valves is a valve resistance. The resistance is then automatically translated into a set-point for field implementation. The optimisation problem has been solved by a non-linear programming solver called CONOPT. The program has calculated time schedules for single and multi-inlet DMAs. The optimal schedules can be translated into centralised flow modulation rules where a set-point for one PRV depends on flows through all other PRVs. For weakly interacting PRVs it is possible to obtain decomposed flow modulation curves where the set-point depends only on the local flow.

The algorithm has been implemented as a module in the Finesse package and allows to solve complete pressure control tasks. Another approach based on GA has been formulated to derive the optimal coefficients of a second order relationship between the flow and the outlet pressure for a PRV. The method has been implemented in Matlab linked to the Epanet hydraulic simulator. The obtained curve can be subsequently implemented using a flow modulation controller in a feedback control scheme. The results of optimal PRV flow modulation via GA has been compared with the time schedule approach using a non-linear programming method described in Chapter 5. The results of both techniques are very close and resulted in almost the same amount of leakage reduction. The main advantage of the flow modulation in comparison to time schedules is that the modulation curves are calculated once and operates robustly over a wide range of demands. Evaluation of optimal control strategies and benefit analysis in terms of leakage reduction for the two case studies provided by Yorkshire Water Services has been included. The results showed that it is possible to reduce the leakage flow by up to 45%.

In order to implement flow modulation strategy a special PRV controller need to be used. Flow modulation PRVs can be operated either hydraulically or electronically to modulate the outlet pressure according to the demand level and required pressure at critical nodes.

The AQUAI-MOD® hydraulic controller is a device to control and modulate the outlet pressure of a PRV according to the valve flow. The controller was experimentally tested via carefully designed experiments to assess its performance and functionality in different conditions and operating ranges. The controller in all cases showed a good performance by modulating the outlet pressure between the minimum and maximum set-points as expected. The dynamic behaviour of the valve was also tested and presented, followed by a detailed explanation. The controller has worked as expected in all tested conditions and it has been found that the dominant dynamic behaviour of the PRV equipped with the AQUAI-MOD® controller is the same as a standard PRV with a standard pilot valve. It is considered that such hydraulic flow-modulated devices could be used to reduce the leakage while satisfying pressure requirements.

The mathematical model of the controller has been developed for both steady state and dynamic conditions. The results of the model has been compared with the experimental data and showed a good agreement in the magnitude and trends. The developed models can be used to compute the required adjustment for the minimum and maximum pressure set-points before installing the controller in the field, or to simulate the behaviour of a PRV and the AQUAI-MOD® hydraulic controller in typical network applications.

It is considered that the experiment design and modelling approach described in this thesis can be helpful for other authors developing mathematical models of similar systems. Such models can be used at the design stage to size the components of a hydraulic controller and to improve its characteristics. They can also be integrated with water network simulators to study the behaviour of WDSs governed by hydraulic flow-modulation controllers.

A method for combined energy and pressure management via integration and coordination of pump scheduling with pressure control aspects has been developed and investigated. The method is based on formulating and solving an optimisation problem and involves utilisation of a hydraulic model of the network with pressure dependent leakage. The cost function of the optimisation problem represents the total cost of water treatment and pumping. Developed network scheduling algorithm consists of two stages. The first stage involves solving of a continuous problem, where operation of each pump is described by continuous variable, and utilises GAMS modelling language and CONOPT3 non-linear programming solver. Subsequently, in the second stage continuous pump schedules are discretised.

The selected case study was the Oldham water supply system, which is a part of United Utilities (UU). Network topology and current operation is described, followed by description of the process of obtaining the network model for scheduling. A comparison has been made between the cost of the current network operation and the optimised operation. Taking into account the costs associated with KWh usage of scheduled pumping stations and assuming summer tariff, the optimised operation reduced the daily electricity cost from 11 to 35% of the current operation for different scenarios. By reviewing and analysing the results of 7 days optimal schedules, it is noticed that the pump flows and the reservoir trajectories have cyclic patterns especially after the second day.

The optimal feedback rules have been derived by GA to control the operation of pump stations. Each pump station has a rule described by two water levels in a downstream reservoir and a value of pump speed for each tariff period. The lower and upper water levels of the downstream reservoir correspond to the pump being ON or OFF. The approach has been applied to Oldham water supply system and the results have been compared with the results of traditional time schedule approach. For both results of optimal feedback rules and optimal time schedule, the system is pumping more water in the period of cheap tariff cost by increasing the speed of variable speed pump. The achieved cost for the feedback control is only slightly higher than that for the time schedule approach but both have very similar energy cost per 1 Ml of pumped water. The feedback control by its nature is more robust and performs well in the presence of uncertainty in water demands and in inaccuracy of hydraulic models. In the considered case study, the optimal feedback rules had advantage of long time of continuous operation of the pumps and the small number of switching, which increase the pump stations life time and reduce the maintenance cost as well.

A sensitivity studies of the derived optimal feedback control rules to the demand levels, the initial reservoir levels and the simulation time horizon have been conducted, and the results showed that the derived rules can operate the system near optimum for the demand varying between 95% and 105% of the original demand. Due to this finding, the optimal feedback rules should be derived seasonally to cope with the demand changes. Changes of the initial reservoirs levels do not show any undesired effect, because the rules are calculated using 7 day horizon removing the effect of the initial reservoirs levels on the obtained results. A quite similar fitness values have been obtained by derived the rules over 1 week and 4 weeks as a simulation time horizon, but with significant changes in the switching levels and pump speeds. Due to this finding, it is recommended to drive the optimal feedback rules using long simulation time horizon.

10.1 Original Contributions to Knowledge

The work presented within this thesis includes contributions that are considered to present significant and original advances over the existing work. There are many novel aspects of the proposed approaches.

- Two different sophisticated methods of calculating the optimal time schedules and flow modulation curve of PRV outlet pressure for the boundary and internal valves have been developed taking into account pressure dependent leakage. One methodology based non-linear programming method utilizing a third party solver to find the optimal time schedule of the PRV setting, while in the second methodology, GAs have been employed as a solver of the optimal PRV flow modulation problem.
- An embedded hydraulic local controller of PRV, AQUAI-MOD® controller was introduced. The controller has been experimentally tested and the behaviours of the coupled system of the PRV and the controller in steady state and dynamics have been evaluated. Full phenomenological mathematical model, which

represents static and dynamic properties of the controller coupled with PRV has been developed. The developed model has been solved and validated using the experimental measurement data.

- Integration algorithm between pump scheduling for energy management and pressure control for leakage reduction has been investigated. A methodology based on non-linear programming has been introduced to find the optimal continuous time schedule for the operation of the pump stations. A sophisticated heuristic algorithm to discretize the optimal continuous time schedule has been developed.

An advanced method to synthesize optimal feedback control rules for pump operations has been developed taking into account a time varying tariff.

10.2 Future Work

The current study has solved and answered some research questions, it also has opened the door for other related research questions that could not be answered, and studies that could not be conducted here due to the limitation of the time.

1) In the pressure control area, a study of dynamic effects of the interacting PRVs in multi inlet DMA should be carried out to provide advice for industrial practice.
2) Further investigations are required to calculate centralise control surface using GA for DMA of many inlet and multi internal PRVs. For a DMA with many inlet multi internal PRVs, the centralized flow modulation surface for one PRV is a relationship between the optimal outlet head of this PRV and the flows through all PRVs in the DMA.
3) It will be necessary to simplify the mathematical model of AQUAI-MOD® controller to use it in the simulation software of water networks. Model simplification could be carried out by ignoring inertia and friction forces in the three moving parts, and all transient terms in the system of equations as well ignoring the head losses in all short connecting pipes. These simplifications lead to a steady state model, which can be used in pipe network simulation models.

4) For further generalization, optimal pump schedule should include the water age and quality issues in the network while solving the optimal pump schedule in both time schedule and optimal feedback control rules are required.
5) Further investigations are required to derive the optimal feedback rules for the operations of pump stations based on the tariff periods and the peak demand periods. Also, study the effects of using longer simulation time horizon on the derived optimal rules is required .
6) Using switching levels only to control the fixed speed pump may result in inefficient operations because it does not consider the periods of cheap and expensive tariff of energy cost, therefore it is recommended for further investigations to drive different switching levels for different tariff periods.

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Appendices

I Appendix A

In this appendix, brief descriptions of GAMS code, CONOPT 3 and software implementation are presented.

I.1 The equation-oriented programming language (GAMS)

GAMS has a notation very close to the original mathematical problem formulation, but in a form that can be compiled and executed by a computer. Therefore the network scheduling problem formulated above has been directly implemented using the GAMS language. The collection of statements written in the GAMS language in order to solve a problem is called the GAMS model. The GAMS model is automatically translated into a form that can be executed by a numerical solver. CONOPT3 has been chosen as the solver in this case, but another solver such as MINOS could be invoked instead. The results from the numerical solver are automatically returned to GAMS and GAMS outputs the results. This fully automatic process is illustrated in Figure I.1.

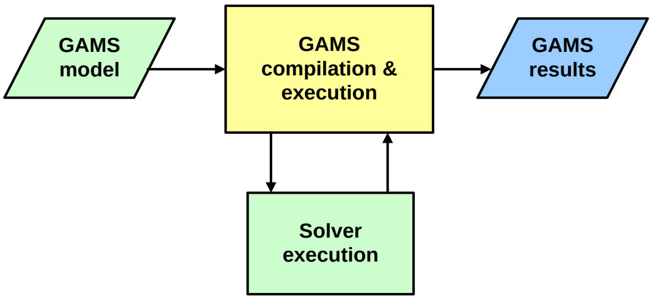


Figure I.1. System model of GAMS and solver

A complete GAMS model is composed of two main parts: data and symbolic equations, as shown in Figure I.2. The data are substituted to symbolic equations only by invoking the numerical solver. There are several key words of the language which identify important components of a model. The main key words will be discussed in the following order: SET, PARAMETER, TABLE, VARIABLE, EQUATION, MODEL and SOLVE. Sets are the basic building blocks of a GAMS model. These correspond to the indices used in algebraic statements.

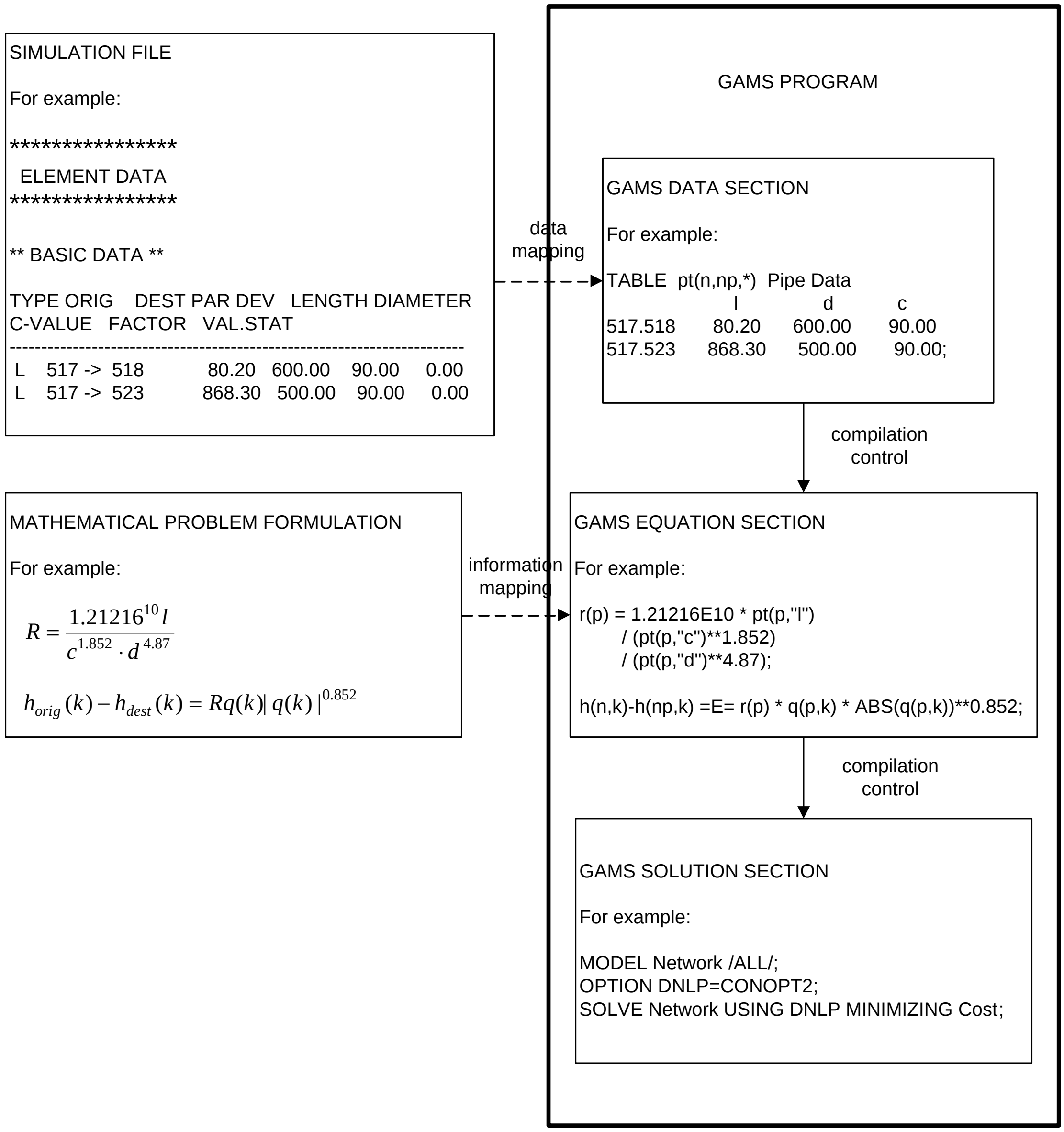


Figure I.2 The structure of GAMS program, i.e. its compilation of control from data to equations and solution. Also the mapping of simulation data to GAMS data and problem formulation to GAMS equations.

To illustrate how data are implemented to GAMS some examples are given below

```
SETS
k  Time intervals
/ 1*24 /
n  Node numbers
/ 517, 518, 523 /
p(n,n)  Pipes
```

```
/ 517.518, 517.523 /
ALIAS (n, np);
```

Four sets have been defined: k, n, p and np. The k, n and np sets are one-dimensional, while p is a two-dimensional set for pipes which is formed from the members of the node set n. The textual comments indicate the meaning of the sets, k contains time intervals, n contains node numbers, and p contains pipes connections between nodes. ALIAS allows the node set to be given another name np. This will prove useful in equations when referencing each node against all other nodes. The network data can be defined in tabular form indexed over the sets:

```
TABLE   pt(n,np,*)   Pipe Data
                  l           d           c
517.518      80.20      600.00       90.00
517.523     868.30      500.00       90.00;
```

Here is a two dimensional table for pipe data called pt. The first two numbers are node numbers from sets n and np and the remaining numbers belong to labels l, d and c. The label l is for pipe length, d is for pipe diameter and c is for pipe c-value. Moreover, by far the majority of the information in all the data tables of the GAMS scheduling model is the same as that found in data tables for the well-known hydraulic simulators. Derive parameters, such as pipe roughness, can be computed from the basic data using indexed expressions:

```
PARAMETER
r(n,n)  Resistance of pipes;
r(p) = 1.21216E10 * pt(p,"l")/(pt(p,"c")**1.852)/(pt(p,"d")**4.87);
```

The first parameter r is declared to be a two dimensional set and documented to stand for pipe resistance. The second statement assigns the values of the Hazen-williams resistance equation for pipes to r(p). Note the SET p and the TABLE pt were declared earlier. The length, diameter, and c-value of pipe p from table pt is represented as pt(p,“l”), pt(p,“d”)., and pt(p,“c”).

Variables and equations can also be defined over sets as following

```
FREE VARIABLES
q(n,n,k)   Flow in elements
h(n,k)    Head at nodes;
EQUATION
pe(n,n,k)  Pipe equation;
pe(p(n,np),k)..
h(n,k)-h(np,k) =E= r(p) * q(p,k) * ABS(q(p,k))**0.852;
```

In the code above, two new state variables are declared for flow and head, q and h respectively. These are used in the pipe equation. Flow and head vary over time k. The pipe equation is declared as pe(n,n,k). Compare how close the implementation of this equation is with the notation of equation (3.7), which formulated previously in Chapter 3.

Finally, any basic lower and upper bounds on variables are also defined as

```
h.LO(n,k) =  25.00;
h.UP(n,k) = 525.00;
```

Here the lower and upper heads for all nodes and at all times are set to 25.0 and 525.0 respectively.

A Model is then defined as a set of equations and the variables they contain. The algorithm that solves the optimisation problem is chosen in the "OPTION" statement and then the optimisation process is started with a "SOLVE" statement:

```
MODEL Network /ALL/;
OPTION DNLP=CONOPT3;
SOLVE Network USING DNLP MINIMIZING Cost;
```

The definition of the model is completely separate from the solution algorithm. An alternative solver can be invoked by changing this single OPTION statement in GAMS and so it is easy to experiment with different algorithms to find one that is best suited to the network scheduling problem.

I.2 The Non-Linear Programming Algorithm

CONOPT solves large non-linear programming problems of the form

$$\begin{aligned} &\text{max (or min) } z = f(x) \\ &\text{subject to} \quad \begin{cases} g_i(x) \le b_i, & i = 1, \ldots m \\ h_j(x) = 0, & j = 1, \ldots n \end{cases} \\ &\text{where} \quad a \le x \le b \end{aligned}$$

where x is a vector of algebraic variables, a and b are vectors of lower and upper bounds, f, g and h are the nonlinear functions that define the model. CONOPT uses generalised reduced gradient algorithm.

In GAMS, f is simply the GAMS variable to be minimised, g and h represent the non-constant terms of the GAMS equations, a and b represent lower and upper bounds in GAMS.

I.3 Advantages of GAMS and CONOPT

- High-level Modelling Systems aid rapid software development. Firstly, the program written in the GAMS language is very short compared to a program written entirely in FORTRAN or C/C++. Secondly, using GAMS there is no need to implement a new algorithm because well tried and tested algorithms, such as CONOPT and MINOS, can be simply invoked and executed by the modelling system.
- It is possible to use non-linear hydraulic model which is accurate over a wider range of conditions. It is not essential to linearise the hydraulic equations.
- CONOPT3 is fast.
- The scheduler can use the same detailed network model as used for the simulator.

I.4 Disadvantage of GAMS and CONOPT

- Algorithm is sensitive to initial starting point. CONOPT3 requires all decision variables to be initialised, in our case performing a hydraulic simulator.
- CONOPT3 produces a set of schedules with continuous values. However, it was found by experiment that the optimal continuous problem is close to the optimal discrete solution.
- The scale of the problem is limited to the number of decision variables which includes both control and state variables – for very large models requires automatic model simplification. The simplifier is based on sound mathematical principles and

automatically reduces the number of pipes in a network model while maintaining the original hydraulic behaviour.

- GAMS is not specialized for water systems, and error messages not domain specific. Deep knowledge of GAMS is required.

I.5 Software implementation

Developed energy and pressure management continuous scheduler has been integrated into a modelling environment, Finesse. The scheduler, as with all tools in Finesse, is general purpose in that it takes any data model of a network, simulates the network to initialise its decision variables for the network scheduler, and if the model is feasible it calculates the optimal continuous schedules. Using a model of a network Finesse automatically generates optimal network scheduling problem written in a mathematical modelling language called GAMS, which calls up a non-linear programming solver CONOPT3 to calculate a continuous optimisation solution. An optimal solution is feedback from CONOPT3 into Finesse for analysis and/or further processing.

Developed user interface (illustrated in Figure I.3) allows to choose: the time step τ_c, presence of pressure dependent leakage (i.e. term $l_c(k)$ in equation (3.17)), whether power consumption for pumps is calculated from pump efficiency or by using the formula given in equation (3.13), CONOPT3 options for tolerance and iteration limit.

Optimisation results are presented in the form of graphs: control and flow for elements (e.g. pumps), head and demand for nodes, as shown in Figure I.4. Obtained schedules can then be fed back into the Finesse input model, or exported to a text file.

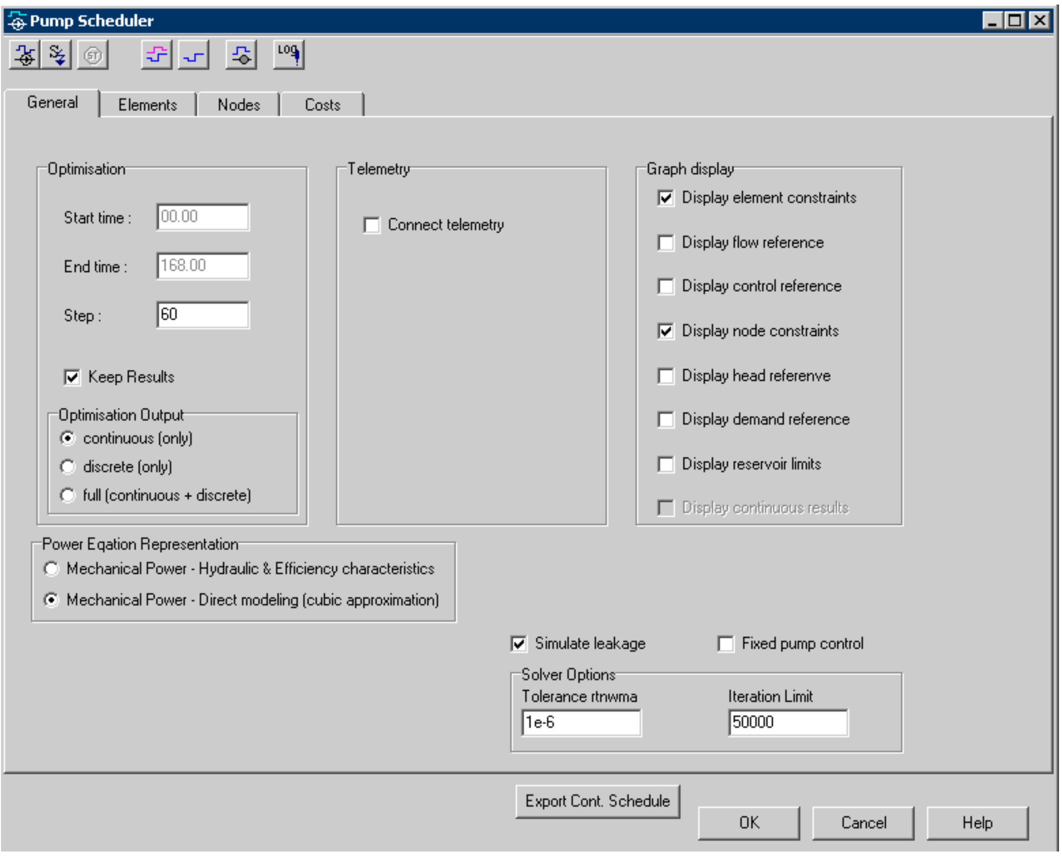


Figure I.3 Finesse: user interface of network scheduler.

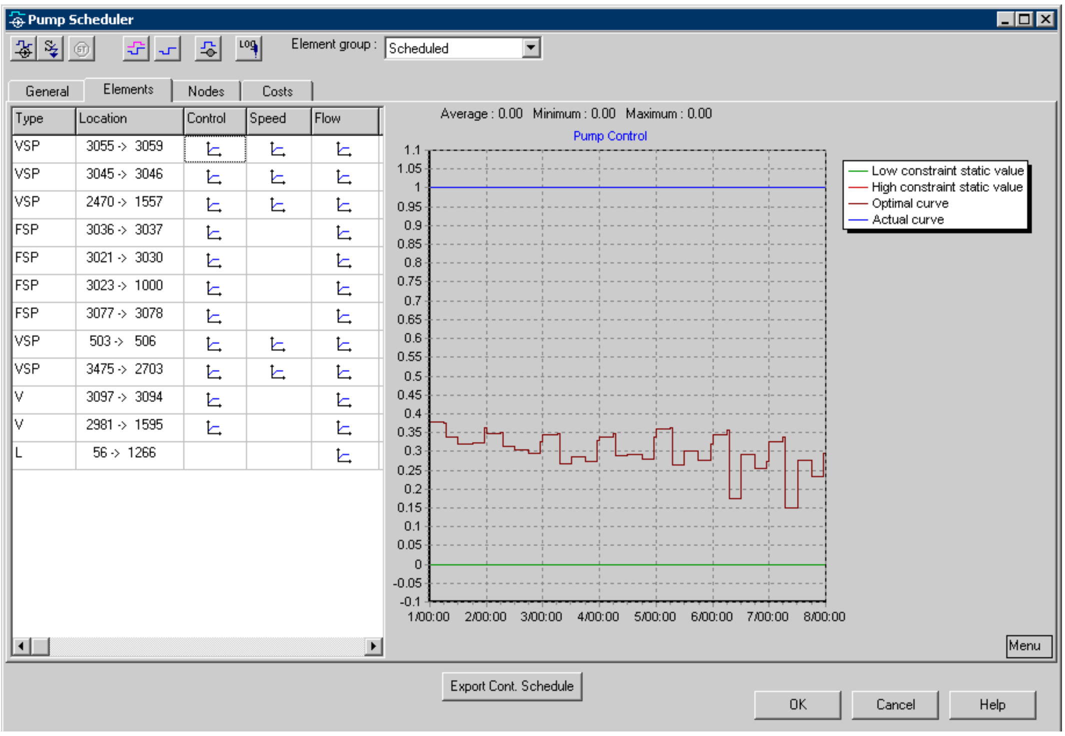


Figure I.4. Finesse: visualisation of optimisation results

II Appendix B

In this appendix, detailed information about the network of Oldham water supply system is provided. In addition, a model description and simplification are also discussed.

II.1 Oldham Case Study

United Utilities• (UU) obtains water from various sources including reservoirs, rivers and aquifers. A large proportion of water supply flows freely by gravity and does not need to be pumped. However, due to the nature of the water catchment areas, being peaty moorlands or coal measure strata, enhanced treatment methods are required to ensure the water satisfies all regulatory and quality standards. The untreated water is conveyed to treatment works by aqueducts. Treated water is delivered to the customers through a network of large diameter trunk mains to smaller trunk mains, service reservoirs, water towers and distribution mains. UU owns, operates and manages the water network assets in north west England which include:

- 137 operational and one emergency impounding reservoirs and associated catchments;
- 95 operational and five emergency water treatment works;
- 450 service reservoirs and water towers storing treated water;
- 609 pumping stations; and
- 42,219 kilometres of clean water mains.

UU owns approximately 57,800 hectares of catchment land. The key reason for owning and managing this land is to protect and improve the quality of raw water supplies and thus reduce the risk of non-compliance at water treatment works and avoid unnecessary operating costs.

UU supplies water to four discrete water resource zones covering North West England:-

- Integrated Resource Zone, serving 6.5 million population in south Cumbria, Lancashire, Greater Manchester, Merseyside and most of Cheshire.
- Carlisle Resource Zone, serving 106,000 population.

• Data about UU has been quoted from http://www.unitedutilities.com/

- North Eden Resource Zone, serving 14,000 population.
- West Cumbria Resource Zone, serving 152,000 population.

The supply network within the Integrated Zone has a high degree of inter-connection, and serves 95% of the region's population. The other three zones are relatively small, and are remote from the regional network. Figure II.1 shows the areas covered by each resource zone. UU water supplies come primarily from upland reservoirs and lowland rivers, but are supported by supplies from groundwater and upland streams. In total UU have over 200 water sources and supply around 1900 million litres per day (Ml/d) of drinking water in a normal year but this would be higher in a dry year.

The water industry uses approximately 3% of total electricity production in developed countries such as the United Kingdom. Pumps consume up to 90% of this electrical energy. UU has total electricity power consumption in water supply systems of 2.51×10^6 kWh, which costs £15.1 million per year.

UU has significantly reduced leakage over the last 15 years, more than halving leakage from 960 Ml/d in 1992/93 to 468 Ml/d at 2006/07. This has been achieved through expenditure on a combination of measures in accordance with national best practice. For example UU has:-

- Installed a comprehensive network of 2360 district meters that continuously monitor water use and leakage in each district of around 1300 properties across the region
- Installed 2343 pressure management valves and other pressure reducing methods to optimise water pressure across our distribution networks consistent with satisfying customer requirements
- Employed a large leak detection workforce of around 190 full-time equivalent personnel, who have been trained and equipped with the latest leak detection techniques
- Provided a free telephone service for customers to inform UU of leaks, and a free supply pipe repair service for households
- Maintained a sophisticated leakage information system that receives and analyses 15-minute flow and/or pressure data from over 6000 sites across the region. This identifies the areas where high leakage is occurring and directs leak detection activities

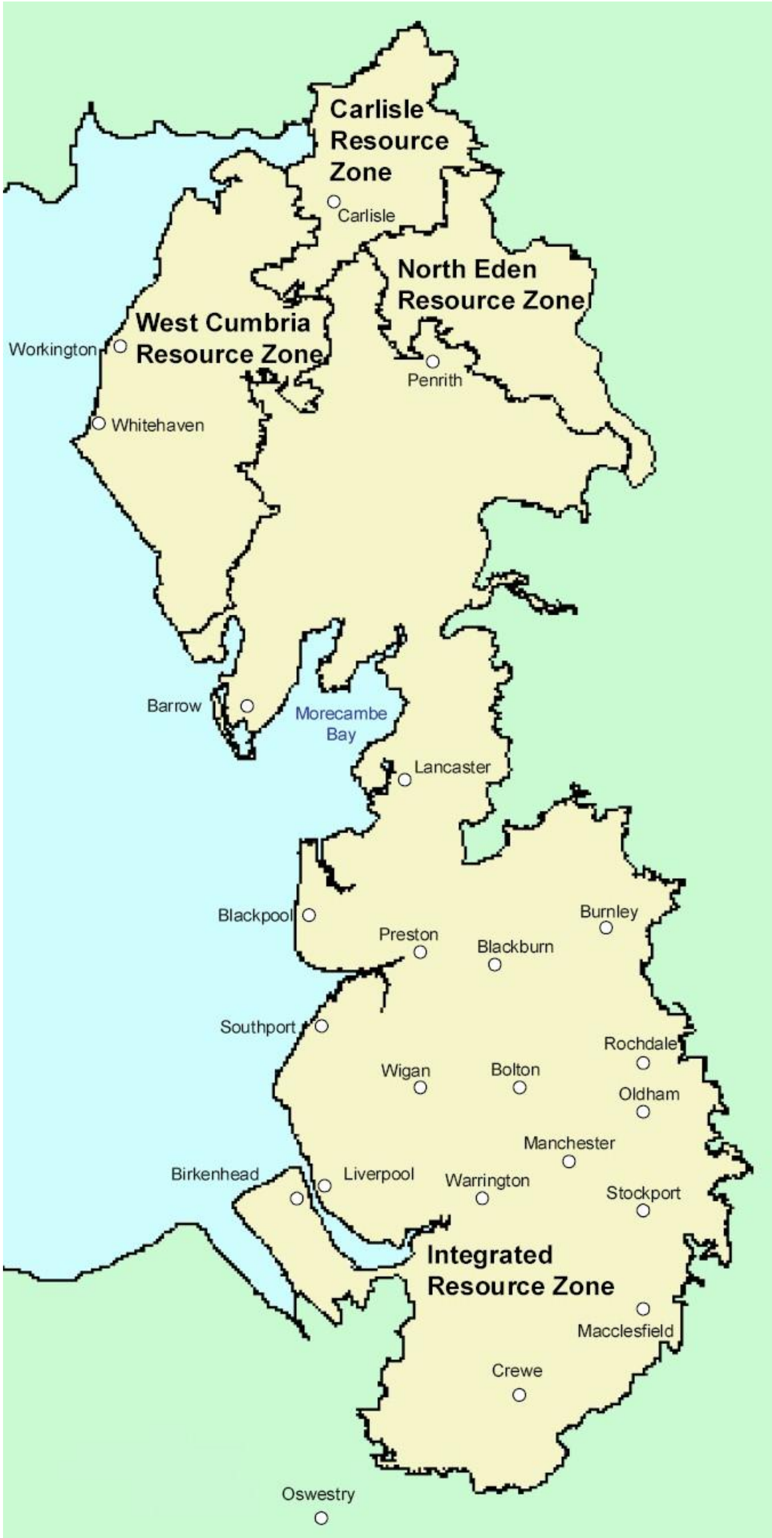


Figure II.1 UU's water supply zones

Due to high pumping power consumption and the leakage level, United Utilities has provided Epanet hydraulic model of the Oldham water supply system as a case study to apply the energy and pressure management algorithms to schedule the operation of pump stations to minimise the pumping cost and reducing the leakage of water while satisfying operating constraints.

II.1.1 Oldham network topology and structure

Oldham is a large town in Greater Manchester, England. It lies amongst the Pennines on elevated ground between the rivers Irk and Medlock, 8.5 km south-southeast of Rochdale, and 11 km northeast of the city of Manchester. Oldham is surrounded by several smaller settlements which together form the Metropolitan Borough of Oldham, of which Oldham is the administrative centre.

Oldham locates in Integrated Resource Zone, as shown in Figure II.1, and its water supply system is connected to the Hawsewater Aqueduct (Manchester Ring Main) delivering water from the Haweswater and Ullswater Lake in the north, Figure II.2. The pressure in the pipe can be supposed to be constant and is 50 m high, and the flow is fixed to 3750 l/s. Oldham water supply system is connected to the Rochdale and the Tameside water supply systems. Figure II.3 shows a schematic of the neighbouring regions. Oldham is also directly connected to Manchester Ring Main through pumping stations Broadway PS and Propps Hall PS and indirectly through Pilsworth PS.

II.1.2 The schematic diagram of Oldham water supply system

The schematic diagram of Oldham water supply system, illustrated in Figure II.4, shows the main elements and components of the system. The schematic depicts the region that has been considered as the energy and pressure management case study. It is mainly Oldham District Metering Zone (DMZ), but contains also some components as well as imports and exports from neighbouring DMZs (Rochdale and Tameside). Oldham water supply system contains

- 4 Water Treatment Works (WTW)
- 4 Feeds from Haweswater Aqueduct (Manchester Ring Main)
- 10 Reservoirs
- 12 Pump stations
- 420 main valves.
- 45 DMAs

Figure II.2. Water sources and Aqueduct lines

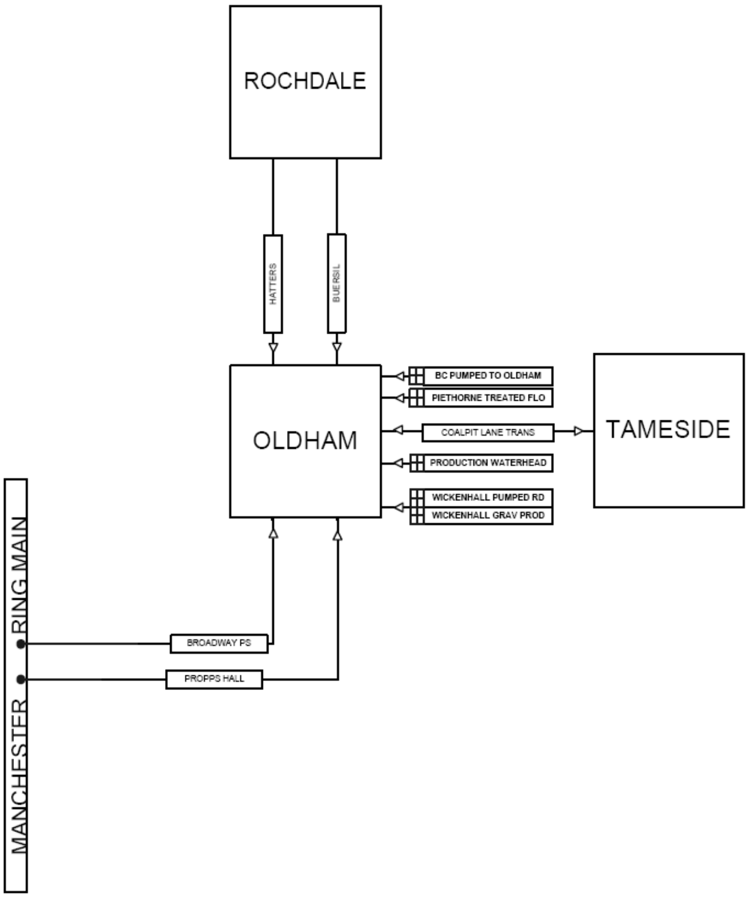


Figure II.3. The connections between Oldham area and Tameside, Rochdale systems and Manchester Ring Main

II.1.2.1 Water sources of Oldham water supply system

As shown in Figure II.4 , Oldham area is supplied by water from different sources, 4 treatment water works and one aqueduct. Table II.1 summarises the capacities, elevations, and water costs at each WTW in Oldham system. Haweswater Aqueduct (Manchester main ring) feeds the Oldham area through four pump stations (Pilsworth PS, Broadway PS, Propps hall PS, and Newmarket Rd PS). Pilsworth PS has two pumps, one is a duty pump and the second is a standby, each has a working capacity of 380 l/s and lifts the water to Hatters SR with average head increase 33 m. Broadway PS is used to support DMAs 243-x demand fulfilling, especially in the summer time, but is mainly off. Propps Hall PS is out of service. Newarket Rd PS supplies Tamesides

DMAs 316-x and Oldham area through Chapel Road Flow valve to feed DMAs 243-x, but is mainly off in normal operation.

Piethorne water treatment works has a maximum design capacity of 20 Ml/d and elevation of 257 m, and it usually produces between 10-20 Ml/d. Its minimum flow through the plant was 5Ml/d, although this is a non-preferred throughput. Piethorne WTW feeds the DMA 240-10 and Oldham Edge SR, and in case of Wickenhall WTW is not running, it feeds also Sholver SR and Readycon Dean SR through Bucktones Rd PS.

Wickenhall WTW design capacity is 16-20Ml/d although it is generally preferred to run at 10-11Ml/d. It supplies Readcon Dean SR through Wickenhall WTW PS, and Sholver SR.

Waterhead TWW capacity is 14Ml/d. There is no clear water reservoir at Waterhead WTW, it gravity feeds into Lowbrook SR via a 1.5km length of 24" trunk main. Buckton Castle WTW has a design capacity of 48 Ml/d and feeds mainly Tameside area and Oldham water supply system by a maximum flow of 14 Ml/d via the Chapel Road Flow valve at the Tameside-Oldham transfer link at Coalpit Lane.

The water cost from Haweswater Aqueduct is the most expensive than the other sources, and it costs twice the average cost in WTWs, so it is recommended to minimize the imported flow from Haweswater Aqueduct and maximise the water production from WTWs.

Table II.1. Water sources of Oldham supply system

Water Sources	Elevation [m]	Capacity [Ml/day]	Cost £/Ml
Piethorn WTW	257	17	25
Wickenhall WTW	300	10	33
Waterhead WTW		14	27
Buckton Castle WTW	216.2	14- to Oldham, 48- total capacity	25
Haweswater Aqueduct	~140 – Average head	~17 to Oldham ~325 – Total flow	57

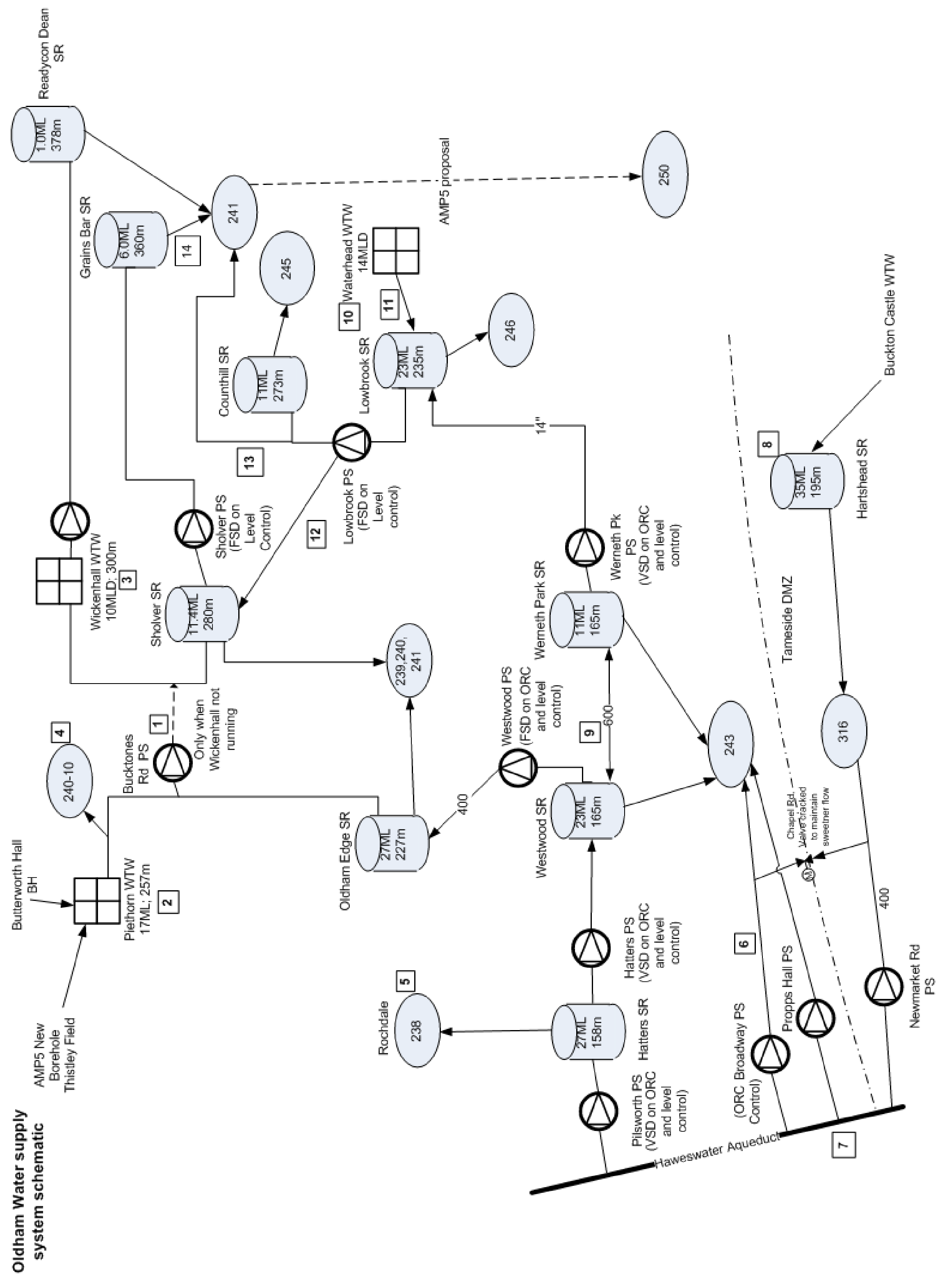


Figure II.4. Schematic diagram of Oldham water supply system

II.1.2.2 Service reservoirs in Oldham water supply system

Oldham water supply system includes ten service reservoirs with different dimensions and capacity. Table II.2 summarises model reference number, elevation, top water level (TWL), hydraulic diameter and full capacity of the service reservoirs in Oldham system. The shapes, physical dimensions and structure of these reservoirs are summarised in Table II.3. The reservoirs are gravity fed or via pump stations and gravity supply the DMAs.

Table II.2 Data of the service reservoirs in Oldham supply system◙

Reservoir Name	Model Ref	Elevation	TWL [m]	Diameter* [m]	Volume [Ml]
Hartshead SR	248T1006	189	6.1	86.68449	36
Hatters SR	BUTa2	151.47	6.42	69.42097	24.3
Westwood SR	X2420066_	158.6	6	67.37284	21.39
Werneth Park SR	X2420061_	158.9	5.7	50.46265	11.4
Sholver SR	X24199FS	274.4	7.1	44.61567	11.1
Readycon Dean SR	X241994S	374.6	4	19.5441	1.2
Grains Bar SR	X24199S6	352.2	5.8	36.59367	6.1
Counthill SR	X2450034_	267.3	5.8	51.11102	11.9
Lowbrook SR	BUTa11	228.8	6.2	66.90945	21.8
Oldham Edge SR	Macc0038	219.8	7	70.46726	27.3

◙ *Data within this table was extracted from the hydraulic model*
* *Equivalent hydraulic diameter*

Hatters SR has a full capacity of 24.3 Ml at a top water level of 6.42 m. It is only fed from Haweswater Aqueduct via Pilsworth PS, and gravity supplies the water supply zone 238 (Rochdale). It also feeds Westwood SR via Hatters PS.

Westwood SR has a full capacity of 21.39 Ml at a top water level of 6.0 m. It gravity supplies zone 243 and Werneth Park SR, and feeds Oldham Edge SR via Westwood PS. Depending on the water level in Westwood SR and Werneth Park SR, the flow between them can be in both directions.

Oldham Edge SR has a maximum water volume of 27.3 Ml at a top water level of 7.0 m. it is fed from Westwood SR via Westwood PS and Piethorn WTW by gravity. It gravity supplies zones 239, 240 and 241.

Werneth Park SR has a maximum water capacity of 11 Ml at top water level of 5.7 m and elevation of 158.9. It is fed from Westwood SR, but the flow can be reversed between these two reservoirs depending on the water level in both. Werneth Park SR gravity supplies zone 243, and feeds Lowbrook SR via Werneth Park PS via 14" pipeline.

Lowbrook SR has a full capacity of 21.8 Ml at top water level of 6.2 m and elevation of 228.8 m. it is gravity fed from Waterhead WTW and from Werneth Park SR via Werneth Park PS. Lowbrook SR gravity supplies zone 246, and feeds Counthill SR via Lowbrook PS.

Counthill SR has a full capacity of 11.9 Ml at top water level of 5.8 m and elevation of 267.3 m. It is fed from two reservoirs, Lowbrook SR via Lowbrook PS and Sholver SR by gravity. The flow from Sholver SR is mixed with the outlet flow of Lowbrook PS to feed Counthill SR. Counthill SR gravity supplies zone 245.

Sholver SR has a maximum capacity of 11.1 Ml at top water level of 7.1 m and elevation 274.4 m. In normal operation it is fed from Wickenhall WTW, and in case of Wickenhall WTW is not running, it is fed from Piethorn WTW via Bucktones Road PS.

Sholver SR gravity supplies zones 239, 240 and 241 as well Counthill SR, also it feeds Grains Bar SR via Sholver PS.

Grains Bar SR has a full water volume of 6.1 Ml at top water level of 5.8 and elevation of 352.2 m. It is fed from Sholver SR via Sholver PS. It gravity supplies the water supply zone 241, but in case of failure of Readycon Dean SR, it feeds this zone via Grains Bar PS (booster pump).

Readycon Dean SR is the smallest reservoir in Oldham water supply zone, it has a maximum capacity of 1.2 Ml at top water level of 4 m and elevation of 374.6. It is fed from Wickenhall WTW via Wickenhall PS, but in case of Wickenhall is not running, it can be fed from Piethorn WTW via Bucktones Road PS. It gravity supplies zone 241.

Table II.3. Shapes, physical dimensions and structure of the reservoirs of Oldham system

Table III.3. Shapes, physical dimensions and structure of the reservoirs of Oldham water supply system*

Site	Data source	Shape	Compartments	TWL	BWL	Operational depth	Each compartment		Diameter (m)	Area (m^2)	Capacity (Ml)	Reported Capacity
							Length (m)	Width (m)				
Westwood	LTAP	Rectangular	2	164.6	158.6	6.0	48.9	36.5	n/a	1782.4	21.4	26.0
	Infobank	Rectangular	2	164.6	158.0	6.6	48.9	36.5	n/a	1784.9	23.6	22.7
Hatters	LTAP	Cylinder	1	157.9	151.5	6.0	n/a	n/a	73.2	4208.4	25.3	27.0
	Infobank	NO DATA	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Hartshead	LTAP	Rectangular	2	195.1	189.0	6.1	66.4	44.6	n/a	2961.4	36.0	35.0
	Infobank	Rectangular	2	264.57	261.47	3.1	66.4	44.6	n/a	2961.4	18.4	35.0
Werneth Park	LTAP	Unknown	2	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	11.4
	Infobank	Unknown	2	164.6	158.9	5.7	n/a	n/a	n/a	999.1	11.4	11.4
Lowbrook	LTAP	Rectangular	2	235.0	228.8	6.2	44.2	39.9	n/a	1761.4	21.8	22.7
	Infobank	Rectangular	2	235.0	228.9	6.1	44.2	39.9	n/a	1761.4	21.5	22.7
Oldham Edge	LTAP	Rectangular	2	226.8	220.8	6.0	45.7	43.0	n/a	1965.1	23.6	27.3
	Infobank	Rectangular	2	226.8	219.8	7.0	45.7	43.0	n/a	1965.1	27.7	27.3
Sholver	LTAP	Cylinder	2	281.5	274.4	7.1	n/a	n/a	31.4	773.9	11.1	11.4
	Infobank	Cylinder	2	281.5	274.5	7.0	n/a	n/a	n/a	n/a	n/a	11.4
Counthill	LTAP	Square	2	273.1	267.3	5.8	32.0	32.0	n/a	1024.0	11.9	11.4
	Infobank	Square	2	273.1	267.4	5.7	32.0	32.0	n/a	1024.0	11.7	11.4
Readycon Dean	LTAP	Square	2	378.6	374.6	4.0	12.0	12.0	n/a	144.0	1.2	1.0
	Infobank	Square	2	378.6	373.9	4.7	12.0	12.0	n/a	144.0	1.3	1.0
Grains Bar	LTAP	Square	2	358.0	352.2	5.8	23.0	23.0	n/a	529.0	6.1	6.0
	Infobank	Square	2	358.1	354.0	4.1	23.0	23.0	n/a	529.0	4.4	6.0

* *LTAP data source is more accurate than Infobank*

II.1.2.3 Pump stations in Oldham water supply system

Oldham water supply system includes eleven pump stations and one booster pump of different types and capacities as summarised in Table II.4. The pump stations left water from water sources or reservoirs to feed other reservoirs, while the booster pump left water from reservoirs to feed high elevation water supply zones.

Table II.4 Data of the pump station in Oldham water supply system

Pump Station	No. of pumps	Type of driver*	Model Ref	Average Flow / Head	Controlled by reservoir level	Control level ON/OFF
Hatters PS	2	VSD	X2420052_ X2420053_	260/38-Duty Off-Standby		
Westwood PS	2	VSD	X2420011_ X2420014_	Off-Standby 196/75-Duty	Oldham Edge	4.5/6.5
Broadway PS	1	FSD	X2420073_	Off-Duty		
Werneth Park PS	1	VSD	X2420075_	Off-Duty	Lowbrook RS	3.5/6.0
Grains Bar	1	VSD	X2419988_	Off-Booster		
Sholver PS	3	FSD	X2410361_ X2419963_ X2419936_	27/97-Duty 27/97-Assist Off-Standby	Grains Bar	2.1/2.8
Wickenhall WTW	2	FSD	X24199A8_ X241998C_	Off-Standby 15/80-Duty	Readycon Dean	2.0/2.4
Bucktones Road PS	2	FSD	X24199D1_ X241996F_	Off-Standby Off-Duty		
Lowbrook PS	2	FSD	X2450024_ X2450028_	70/50-Duty Off-Standby	Counthill RS	4.9/5.4
Pilsworth PS	2	VSD	PILWTH PILPMP2	380/33-Duty Off-Standby	Hatters SR	5.3/5.73
Newmarket Rd PS	1	VSD	NEWMRKT	Off-Duty		
Propps Hall PS	is not used anymore					

* *FSD stand for fixed speed driver, VSD stand for variable speed driver.*

Pilsworth PS has two variable speed pumps, one is a duty pump and the second is a standby, of average working capacity of 380 l/s with delivery head of 33 m. Pilsworth PS lifts water from Haweswater Aqueduct (Manchester main ring) to Hatters reservoir. It is controlled by Operational Response Centre (ORC) and the water level of Hatters SR.

Propps Hall PS is used to support the water supply zone 243, but is not used anymore.

Broadway PS is one fixed speed duty pump and on ORC control. It is used to support the water supply zone 243 demand fulfilling, especially in the summer time, but is mainly off. It lefts water from Haweswater Aqueduct to feed directly WSZ 243.

Newmarket PS is one variable speed duty pump and on ORC control. It lefts water from Haweswater Aqueduct to feed directly water supply zones 316 and 234 via the Tameside-Oldham transfer link at Coalpit Lane in case of Buckton Castle WTW failure or is not running, but is mainly off.

Hatters PS is two variable speed pumps, one is a duty and the second is a standby pump, and is controlled by ORC and the water level of Westwood SR. It has an average working capacity of 260 l/s at delivery head of 38 m. It lefts water from Hatters PS to feed Westwood SR.

Westwood PS has two variable speed pumps, one is a duty and the second is a standby pump, and is controlled by ORC and the water level of Oldham Edge SR. It works on average flow and head of 195 l/s and 75 m, respectively. It lefts water from Westwood SR to supply Oldham Edge SR.

Werneth Park PS is one variable speed duty pump, and is controlled by ORC and water level in Lowbrook SR. It lefts water from Werneth Park SR to feed Lowbrook SR.

Lowbrook PS includes two fixed speed pumps; one is used as a duty and the second as a standby pump, and is controlled by ORC and the water level of Counthill SR. It delivers on average a flow and head of 70 l/s and 50 m, respectively, from Lowbrook SR to feed Counthill SR.

Bucktones Road PS includes two fixed speed pumps; one is a duty and the second is a standby pump, and under ORC control. It cannot be run at the same time as Wicken Hall WTW. It is used to pump water from Piethorn WTW to feed Sholver SR and Readycon Dean SR, in case of Wickenhall WTW is not in operation.

Sholver PS includes three fixed speed pumps, one is as a duty, the second is an assist and the third is a standby, and is controlled by the water level of Grains Bar SR. The both pumps, the duty and assist pumps, are running to deliver an average flow and head of 27 l/s and 97 m, respectively, from Sholver SR to supply Grains Bar SR.

Wickenhall PS has two fixed speed pumps, one is a duty and the second is a standby pumps, and is controlled by the water level of Readycon Dean SR. It lefts water from Wickenhall WTW to feed Readycon Dean SR with average flow and head of 15 l/s and 80 m, respectively.

Grains Bar is a variable speed booster pump used as a standby to feed DMA 241_11 in the event that supply from Readycorn Dean SR is not possible.

II.1.2.4 Water supply zones and DMAs in Oldham area

Oldham water supply system includes 60 DMAs and export nodes, but that only 45 DMAs are fed directly from the Oldham/Tameside trunk mains. The Water supply zones and DMAs in Oldham area are highly interconnected. The total demand of the DMAs and the exported flow is 63.2 Ml/d. The demand pattern, Figure II.5, has two peaks, the first has a maximum value of 85.5 Ml/d (990 l/s) occurs at 8:15 am,

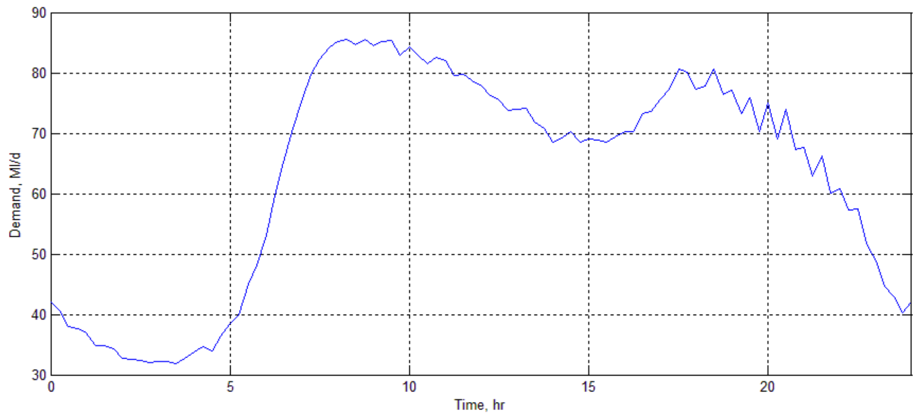


Figure II.5 Daily total demand and exported flow of Oldham water supply system

the second peak has a maximum value of 80.4 Ml/d (930 l/s) at 18:30, and the minimum demand occurs at 2:30 am and has a value of 32 Ml/d (370 l/s). The total demand of Oldham Water Supply System is in average 56.8 Ml/d and varies depending the season around 12-15%. In most cases, water is gained from WTWs within Oldham region, pumped to reservoirs that are on a higher level than the connected DMAs and provided to customers via gravity. A defined minimum reservoir level ensures that pressures at the DMA inlets are always fulfilled.

II.2 Current Operation Policy

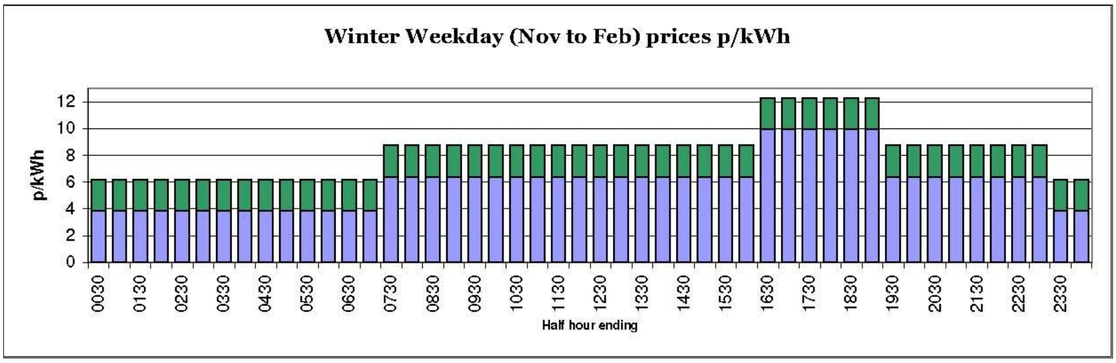
In most cases, water is gained from WTWs within Oldham region and pumped to the reservoirs. The ellipses (243, 241, etc.) in the schematics represent several DMAs. PRVs can be within DMAs to avoid too high pressures, but have not been scheduled in this case study, hence each DMA is represented by one node. Water supply of some DMAs (e.g. 243) can be supported by direct pump operation, but in case of Broadway PS and Propps Hall PS should be avoided as water from Manchester Ring Main is twice as expensive as water from other WTWs. Broadway PS is used to support DMAs 243-x demand fulfilling especially in the summer time, but is mainly off. Propps Hall PS is out of service. Rochdale is fed by Hatters SR that can only be fed from Manchester Ring Main. Water from Tameside DMZ is delivered to Oldham by adjusting Chapel Road Flow valve and fixing flow into Oldham. The exported flow from Oldham to Rochdale DMZ (Buersil transfert) is also kept constant at 5Ml/d.

UU should be maximising Buckton Castle WTW output and pushing this into Oldham via the Tameside-Oldham transfer link at Coalpit Lane, at the expense of less Aqueduct pumping. Likewise, maximise Waterhead WTW output and cut back on Werneth Park pumping as it has been pumped several times before it gets to Werneth Park PS (unless it has come from Buckton Castle)

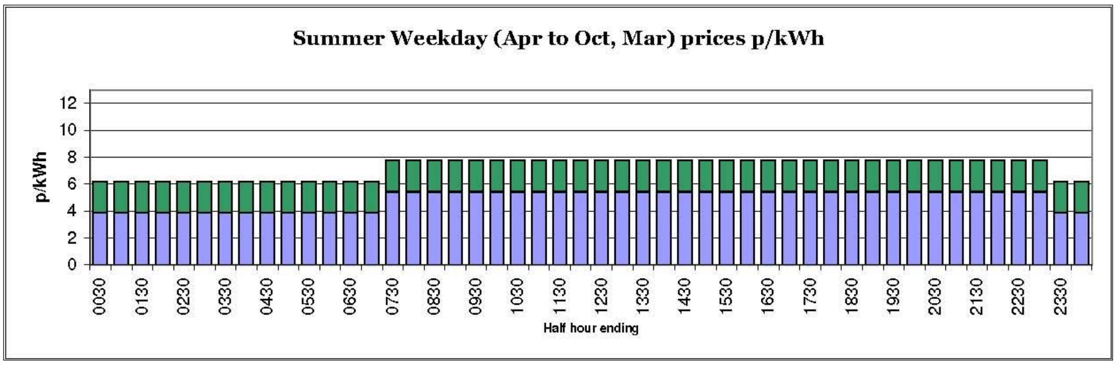
Piethorne usually produces between 10-20Ml/d. Its minimum flow through the plant was 5Ml/d, although this is a non-preferred throughput. The rapid alteration of flow rates through WTW should be avoided as this has the possibility of putting the process “at risk”. WTW should be kept pretty much constant with rates of change of output restricted to ±1ML per day.

II.3 Energy Tariff

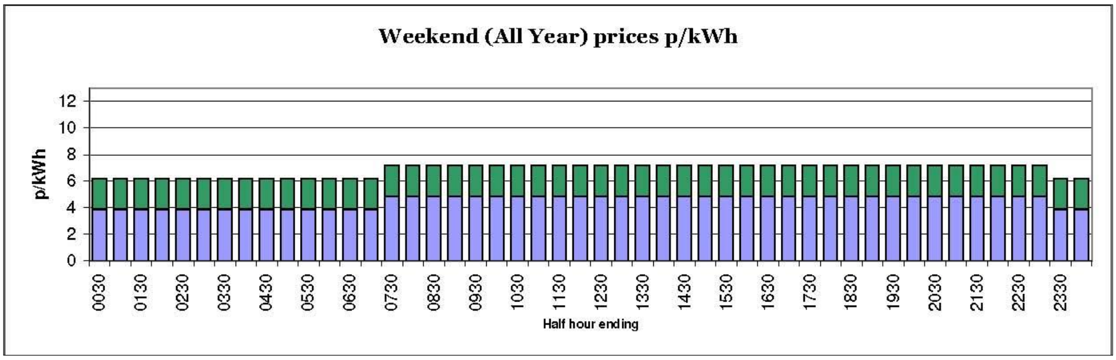
The electrical cost is the consumption charge (£/kWh), i.e., the cost of electrical energy consumed during a time period. The consumption charge usually varies depending on the time of the day, with peak and off-peak electricity tariffs. Electricity seasonal time of day and trading cost, electricity tariff, is provided and covers all seasons of year 2008/2009. In this study, summer tariff only is used to calculate the pumping cost, hence the demand and telemetry data are provided for the first week of August 2007. Figure II.6 presents the electricity tariff for the same year. Electricity tariff on the summer week day, Figure II.6-b, has two different cost per day, off-peak and peak tariffs. The peak tariff period extends from 07:00 to 23:00 of electricity cost of 7.753 p/kWh, while the off-peak tariff period covers the rest of day, and extends from 23:00 to 07:00, and has an electricity cost of 6.204 p/kWh.



(a)



(b)



(c)

Figure II.6 Electricity tariff for 2008/2009

II.4 Hydraulic model

UU provided a working Epanet hydraulic model of the Oldham water supply system, in plain ASCII text file (inp format). The model covers the Oldham water supply system, a part of Haweswater Aqueduct (Manchester main ring) at the west of the model and a part of Tameside DMZ at the south of the model, as shown in Figure II.7.

Epanet models a water distribution system as a collection of links connected to nodes. The links represent pipes, pumps, and control valves. The nodes represent junctions, and reservoirs.

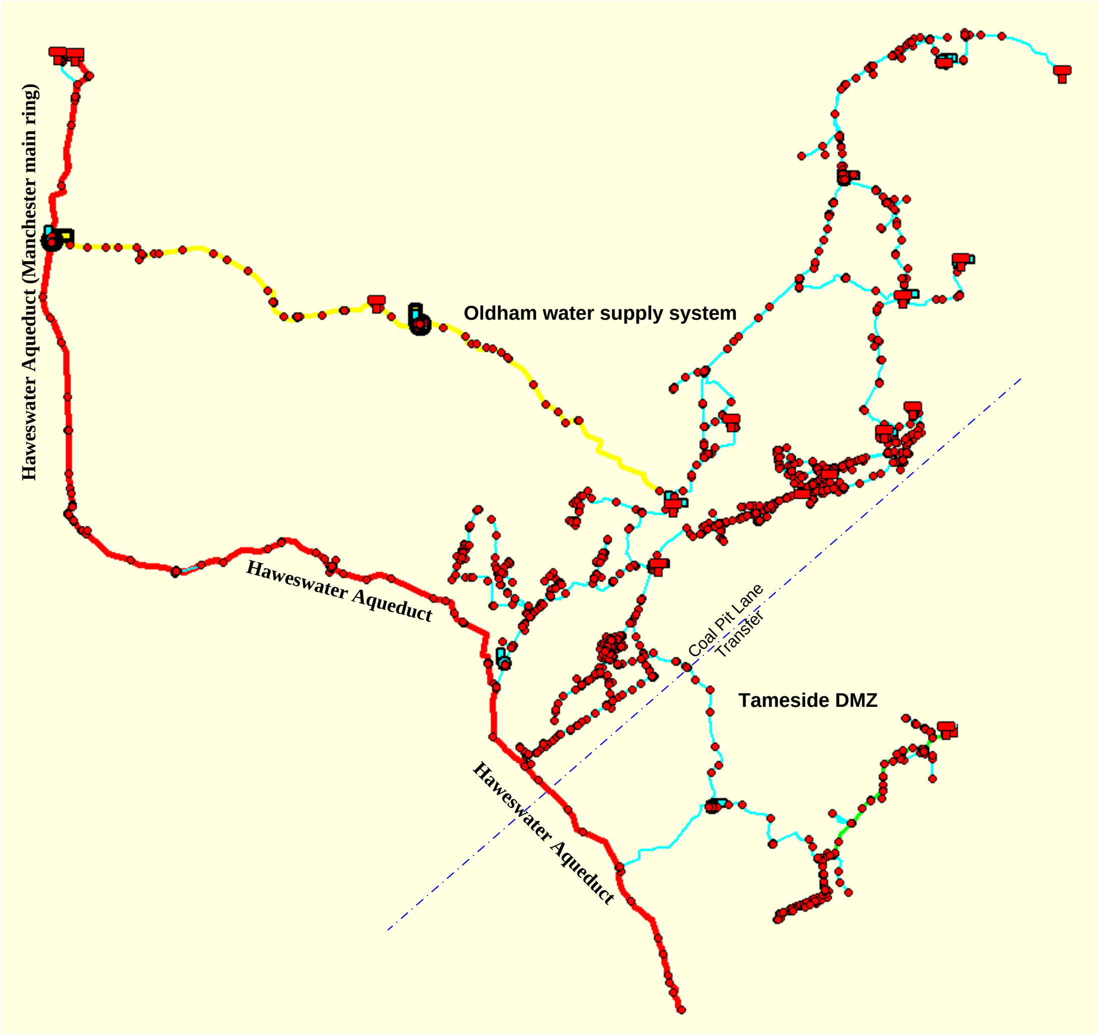


Figure II.7. Epanet hydraulic model of the Oldham water supply system

Oldham hydraulic model includes 3535 junction nodes, 45 of them represent the DMAs of Oldham area. The model includes 3279 main pipes of total length 154 km. The provided model includes 5 reservoirs, 3 fixed and 2 variable head reservoirs according to a given pattern, and 12 variable head reservoirs. The model has 11 pump stations of 19 pumps, 7 variable speed and 12 fixed speed pumps, one of them is a booster pumps. The model includes 418 valves of different type, 348 valves are fully opened, 50 are completely closed and 20 are partially opened. Table II.5 summarises the components included within the Oldham water supply system.

Table II.5. Oldham model summary

Components	Number
Junctions	3535
DMAs	45
Fixed head reservoirs	5
Variable head reservoirs	12
Pipes	3279
Pump stations	11 includes 19 pumps 7 VSP + 12 FSP
Valves	418 2 Flow control valve 1 Pressure reducing valve 12 Pressure sustaining valve 403 Throttle control valve

The DMA nodes are assigned to a demand of typical patterns as depicted in Figure II.8, but vary in the magnitude and the peaks. The demand patterns has two peak periods, the first around 08:00 and the second peak around 18:00. The leakage flow is not simulated as a pressure dependent leakage, but it assumed to have fixed values of a different pattern as shown in Figure II.9. Some patterns are flat or have a constant values, in some other patterns, the leakage flow have a higher values at the night from 21:00 to 05:00, and lower values during the day from 05:00 to 21:00. The model has two nodes of a negative constant demand for imported flow, these nodes represents two water treatment works, Piethorn WTW (model Ref. 23999801) of 9.5 ml/d and Waterhead WTW (Model Ref. 000F4FEB) of 8.6 Ml/d.

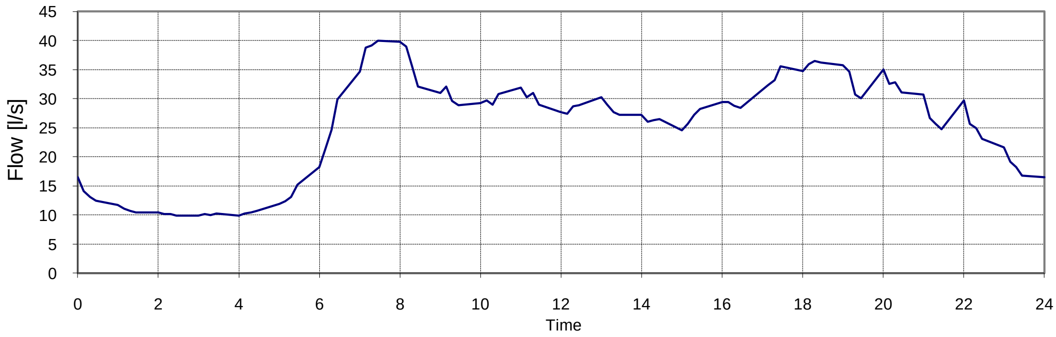


Figure II.8. Typical demand pattern

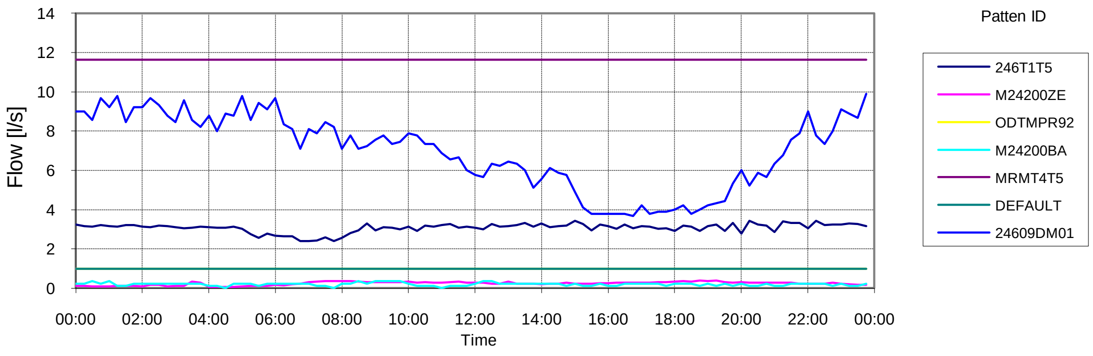


Figure II.9. The leakage patterns

The demand data for all DMAs are taken from 1 August 2007 to 7 August 2007, but some of these DMAs have not accurate measurements in this period, so the demand data has been taken from other periods, as follow

23901DM1 - data provided for same period from previous year (Aug 2006)

24309DM1 - data provided for same period from following year (Aug 2008)

24313DM1 - data provided for first week of September 2007

24602DM1 - data provided for second week of Aug 2007

II.4.1 Reservoirs

Oldham water supply system includes 5 reservoirs, 3 are fixed head and 2 with pressure or head patterns. Figure II.10 illustrates the locations of service reservoirs in Oldham water supply system. Table II.6 summarises the data of fixed head reservoirs. The reservoir XOLD001 represents the Hawsewater Aqueduct inlet boundary and has a fixed head of 149 m and fixed outlet flow of 3750 l/s (324 Ml/d). The head pattern reservoirs, of model ID references 00014C31 and A00BAF15, are connected to Oldham system via permanently completely closed valves, and have been removed from the model in the current study.

Buckton Castle WTW is represented by a fixed head reservoir, has a model reference 24800001, of a fixed head of 216.2 m and outlet flow changed according to a given pattern. As well, Wickenhall WTW is represented by a fixed head reservoir, has a model reference 24199210, and of fixed head of 300.524 m, and the flow is subjected to the system demand.

Table II.6 Summary of the fixed head reservoirs data

Reservoir Model Reference	Type	Head [m]	Comment
XOLD001	Fixed head	149	Aqueduct inlet boundary
00014C31	Head pattern		Connected via permanently completely closed valve
A00BAF15	Head pattern		
24800001	Fixed head	216.2	represents Buckton Castle WTW
24199210	Fixed head	300.524	represents Wickenhall WTW

Two water treatment works, Piethorn WTW and Waterhead WTW, are represented by normal nodes or junction with negative constant demand.

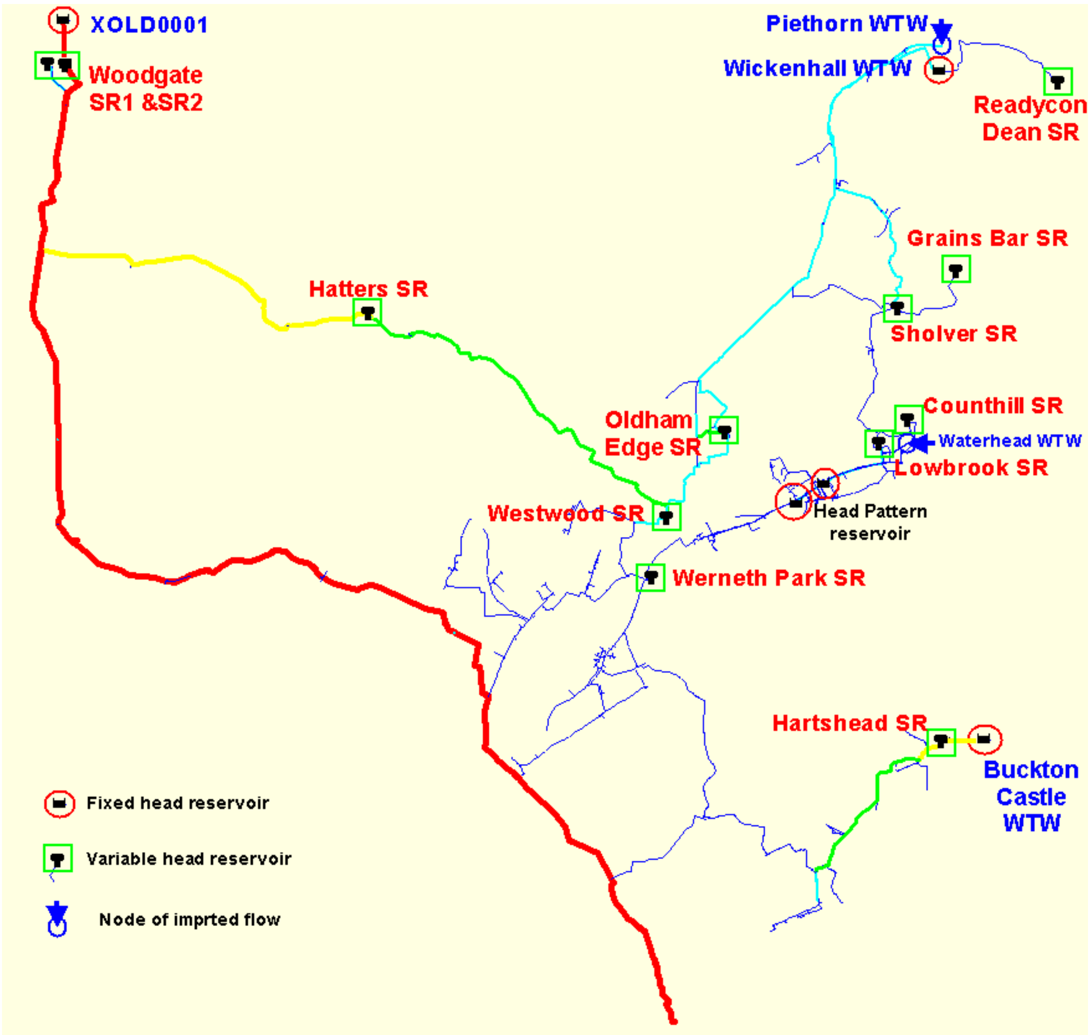


Figure II.10. Fixed and variable head reservoirs in Oldham area

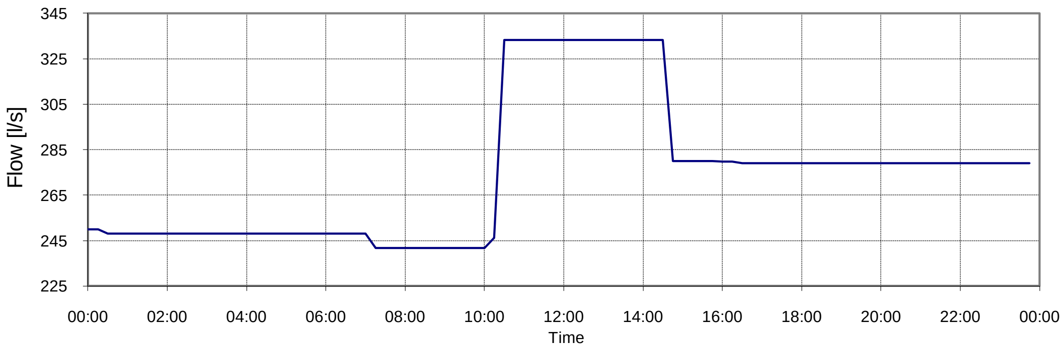


Figure II.11 The outlet flow from Buckton Castle WTW to feed Oldham system

II.4.2 Variable head reservoirs

The Epanet hydraulic model of the Oldham water supply system includes 12 variable head reservoirs. Two reservoirs, Woodgate Hill SR1 and SR2, placed on Hawsewater Aqueduct and have not any effect on Oldham area, and have been removed from the model. Hartshead SR belongs to Tameside DMZ, but has been included within Oldham system. Figure II.10, shows the positions of the variable head reservoir in Oldham area

II.4.3 Pipes

Oldham water supply hydraulic model includes 3279 pipes of total length 154 km, including 32 km the length of Haweswater Aqueduct and 122 km the length of the mains in Oldham supply system and Tameside DMZ. The pipe diameters vary from 30 mm to 1500 mm, and the pipe lengths range from 0.2 m to 1907 m. Table II.7 summarises the pipe diameters ranges and the total length for each range.

Table II.7. The pipe diameter and total length data

Pipe Diameter [mm]	Total length [km]
less than 100	9.05
101 - 200	13.09
201- 350	32.68
351 -600	50.07
601-1500	49.24

II.4.4 Pumps

Oldham water supply system includes eleven pump stations and one booster pump with different types and capacities, Figure II.12 shows the pump station locations in the hydraulic model of Oldham water supply system. The provided hydraulic model does not contain any power or efficiency data for any of pump stations. Either for the pump stations that do not have the manufacture data sheet or the field test data, the peak efficiency has been assumed to be 80% at the operating point for each pump. While for pumps with a proper field test, the power characteristics have been extracted from those tests. For pumps with improper field test, the power characteristics have been extracted from the manufacture data sheets.

All pumps run under ORC control, and some of these pumps are also controlled by reservoir water level. The control rules implemented in the Epanet hydraulic model to control the pump stations operations are discussed in the section “II.4.8”.

Table II.8 shows the pump stations details, number of pumps and types, and model references, and shows the water levels of the reservoirs that control the pump operations.

Table II.8. Pump stations data as represented in the Epanet model

Pump Station	No. of pumps	Type of driver*	Model Ref	Average Flow / Head	Controlled by reservoir level	Control level ON/OFF
Hatters PS	2	VSD	X2420052_ X2420053_	260/38-Duty Off-Standby	Westwood SR	3/6.5
Westwood PS	2	VSD	X2420011_ X2420014_	Off-Standby 196/75-Duty	Oldham Edge	4.5/6.5
Broadway PS	1	FSD	X2420073_	Off-Duty		
Werneth Park PS	1	VSD	X2420075_	Off-Duty	Lowbrook RS	3.5/6.0
Grains Bar	1	VSD	X2419988_	Off-Booster		
Sholver PS	3	FSD	X2410361_ X2419963_ X2419936_	27/97-Duty 27/97-Assist Off-Standby	Grains Bar	2.1/2.8
Wickenhall WTW	2	FSD	X24199A8_ X241998C_	Off-Standby 15/80-Duty	Readycon Dean	2.0/2.4
Bucktones Road PS	2	FSD	X24199D1_ X241996F_	Off-Standby Off-Duty		
Lowbrook PS	2	FSD	X2450024_ X2450028_	70/50-Duty Off-Standby	Counthill RS	4.9/5.4
Pilsworth PS	2	VSD	PILWTH PILPMP2	380/33-Duty Off-Standby	Hatters SR	5.3/5.73
Newmarket Rd PS	1	VSD	NEWMRKT	Off-Duty		

* *FSD stand for fixed speed driver, VSD stand for variable speed driver.*

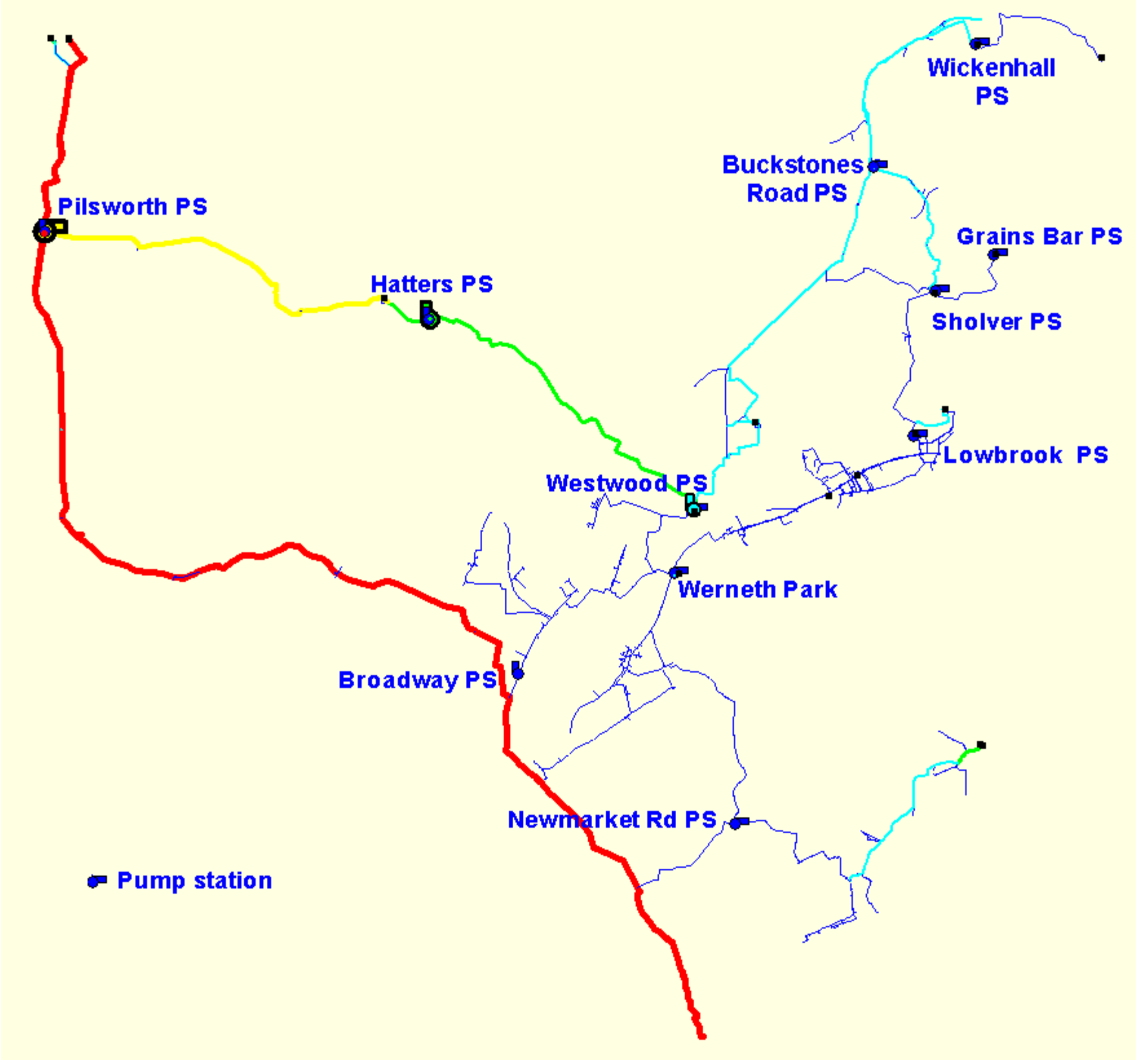


Figure II.12. The locations of the pump stations in Oldham water supply system

II.4.4.1 Pump Characteristics

The hydraulic characteristics (*h-q* relationship) of the pumps are calculated by a second order polynomial.

$$h(q) = Aq^2 + Bq + C$$

while the power are estimated by a third order polynomial.

$$P(q) = s^3\left(E\left(\frac{q}{s}\right)^3 + F\left(\frac{q}{s}\right)^2 + G\left(\frac{q}{s}\right) + H\right)$$

where h is the delivered head [m], q is flow rate [l/s], P is the power consumption [KW], s is relative pump speed and A, B, C, E, F, G, and H are hydraulic and power coefficients that shown in Table II.9.

Table II.9 Hydraulic and power coefficents of Oldham pump stations

Pump St	A	B	C	E	F	G	H
Pilsworth	-3.00E-05	-1.00E-05	3.75E+01	3.00E-06	-3.30E-03	1.31E+00	-1.97E+01
Broadway	-2.56E-03	-1.00E-05	8.14E+01	3.00E-06	-3.73E-04	2.57E-01	4.45E+01
Werneth	-5.91E-04	-2.32E-02	1.56E+02	1.30E-05	-4.77E-03	1.35E+00	1.34E+02
Grains Bar	-2.01E-02	-1.86E-02	2.63E+01	2.30E-05	-6.32E-04	7.92E-02	2.91E+00
Wickenhall	-5.18E-02	-6.52E-02	9.15E+01	7.42E-03	-3.26E-01	4.68E+00	-6.62E+00
Bucktones	-3.80E-03	-3.04E-01	9.39E+01	5.00E-06	-3.64E-04	1.74E-01	3.52E+01
Sholver	-1.51E-02	-4.41E-01	1.20E+02	2.90E-05	-4.91E-04	3.56E-01	2.88E+01
Westwood	-1.21E-03	-2.27E-02	1.30E+02	1.00E-05	-1.54E-03	6.49E-01	8.94E+01
Hatters PS	-2.90E-05	-2.25E-02	4.52E+01	0.00E+00	-1.87E-04	1.73E-01	8.11E+01
Lowbrook	-1.71E-03	-1.54E-03	6.19E+01	2.00E-05	-2.13E-03	3.92E-01	2.59E+01
NEWMRKT	-6.67E-04	-4.92E-02	1.36E+02	3.40E-05	-1.27E-02	2.19E+00	6.68E+01

II.4.5 Valves

The Epanet model of Oldham water supply system includes 418 valves of different types and 23 pipes of check (non-return) valve. Table II.10 summarise the number of each valve type and its state. The most of these valves (348 valves) are permanently fully opened and 50 valves are permanently completely closed, while 20 valves only are partially opened. Most of partially opened valves are located upstream of the variable head reservoirs, to control the inlet flow, and few of them are located downstream the pump stations to control the delivered flow, and some are located in between two reservoirs or on a pipe line to control the flow or reduce the pressure.

Table II.10. Data of the valves included in the Oldham supply system model

Valve type	Total Number	Permanently Fully opened	Permanently Completely closed	Partial active
Flow control valve (FCV)	2	-	1	1
Pressure reducing valve (PRV)	1	-	-	1
Pressure sustaining valve (PSV)	12	0	12	0
Throttle control valve (TCV)	403	0	37	18
Pipes with check valve (CV)	23	-	-	-
All valves types*	418	348	50	20

** the number of all valves types does not include the number of Pipes with check valve*

II.4.6 Minor Losses

The Epanet model of Oldham water supply system has not any pipe element assigned to minor losses, while 392 valves of 418 total valves are assigned to minor losses ranged from 0.12 to 16.5. Table II.11 summarise the data of minor losses setting of the valves included in the model of Oldham water supply system.

Table II.11. Minor losses setting of the valves included in the Oldham model

Minor Losses Coefficient K	FCV	PSV	PRV	TCV	Total
$K = 0$	2	12	0	12	26
$0.12 \leq K \leq 0.4$	0	0	0	92	92
$K = 0.5$	0	0	0	259	259
$K = 1$	0	0	0	26	26
$K > 1$	0	0	1	14	15
					418

II.4.7 Time Patterns

The Epanet hydraulic model of Oldham water supply system includes 1448 time patterns, only 32 time patterns are used to define the demand, leakage and export flow data, and 2 patterns are used to define the head of two fixed head reservoirs. The demand, leakage, and export flow are defined by one or more of the time patterns scaled by factors ranged from 0.001 to 68.91.

II.4.8 Controls

Simple controls are applied in the Epanet model of Oldham water supply area to control the flow through the valve of model references 24800001 to limit the outlet flow from Buckton Castle WTW to feed Oldham area. 96 control statements are used to limit the flow through this valve around the day of 15 minute time interval.

Another set of control statements are used to control 6 pumps, 6 pairs of control statements, each pair has “open” and “close” control statement depending on the water level in the reservoir.

Table II.8 explains and presents the set of control statements that control the pump stations depending on the reservoirs water level. Figure II.13 presents the control links of the pump and corresponding reservoirs.

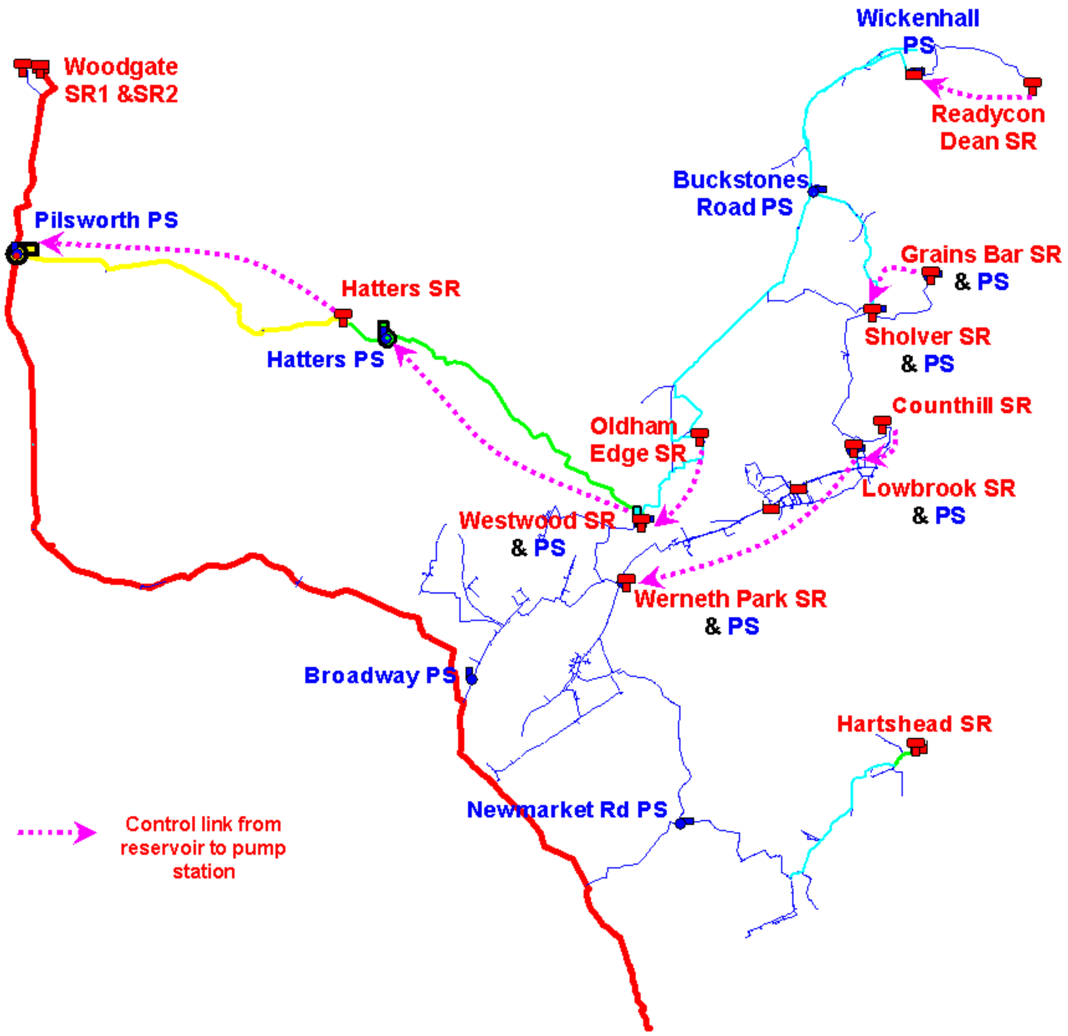


Figure II.13 Schematic of the pump stations controlled by reservoirs water level

Pilsworth PS are controlled by the water level of the Hatters reservoir using 8 rules statements 4 rules for each pump conditioned by both the day time and the reservoir water level.

Another set of 22 rule statements are used to open and close the upstream valves (fill valves) of the variable head reservoirs. Table II.12 summarise all rules that control the fill valves of the variable head reservoirs and the open/close water level.

Table II.12 Variable reservoir fill valve and control levels

Reservoir	Reservoir model Ref.	Fill valve model Ref	Open level [m]	Close level [m]
Grains Bar SR	X24199S6	X2419942_	5.500018	5.790018
Westwood SR	X2420066_	X2420067_	5.500006	5.990006
Werneth Park SR	X2420061_	X2420060_	5.600005	5.690005
Counthill SR	X2450034_	X2450036_	5.549981	5.789981
Hatters SR	BUTa2	ROCHD02	5.920008	6.410008
Sholver SR	X24199FS	X2410541_	6.800013	7.090013
Oldham Edge SR	Macc0038	X2399934_	6.5	6.99
Lowbrook SR	BUTa11	ORRVa12	5.199993	6.5
Woodgate SR2*	MRM00007_	MRM00006	5.150006	6.150006
Hartshead SR	248T1006	248T1001	5.100018	6.090018
Oldham Edge SR	Macc0038	Macc0042	6.5	6.99

* Woodgate SR1 and SR2 are not included in Oldham Water supply system

II.5 Simplified Model

A model is an abstract representation of physical reality. Models represent certain aspects of reality, neglecting other aspects for a particular application. For example, the hydraulic models considered here represent the relationship between flows and pressures in the pipe networks under steady state conditions. They omit the short term dynamic relationships between pressures and flows which is known as transients. Models should be adequate for the application they are aimed at. Currently, with the introduction of GIS systems water companies tend to build so called “all mains models” which include all or nearly all distribution pipes. These models can be very large depending on the area, e.g. up to 3,500 pipes as in Oldham water supply system. They are appropriate for simulation purposes, however optimisation tasks are much more complex and simplified models are required. Algorithms for these tasks are based on search techniques and are equivalent, in terms of computational effort, to solving the simulation model many times. It is necessary to use the simplified models for those applications. There are different methods of model simplification, some are based on common sense others on formal mathematical algorithms. The final product of all of these methods is a hydraulic model with a smaller number of components than the original network. A typical hydraulic simulation model contains thousands of pipes but only few reservoirs, pumps or control elements. Therefore, a common simplification strategy is to reduce the number of pipes. However, it is also possible to replace a number of reservoirs situated in close proximity by an equivalent storage. It is also a common practice to use one pump model for a number of identical pumps connected in parallel or in series. Accuracy is sometimes adversely affected by simplification but the recalibration of the simplified model can increase its accuracy.

II.5.1 Network simplification problem

The network model simplification problem can be expressed as in the following statement: Find a hydraulic model of a network with a reduced number of components, which approximates the mapping between the input and output variables over a wide range of operating conditions, where: input variables are: source inflows, source heads, demands, pump schedules and initial reservoir levels, and output variables are: flows in pipes and heads at nodes over a time horizon.

The reduced model ought to preserve the non-linearity of the original network and approximate its operation accurately under different conditions. It is expected that the relationships between heads and demands are similar in both the full and reduced models. There are three common approaches to model simplification:"element by element", variable elimination and approximation. The" Element by element" method includes two activities: skeletonisation of the structure and the use of equivalent pipes in place of numbers of pipes connected in parallel and/or in series.

The skeletonisation technique eliminates pipes of a small diameter leaving only major pipes in the model. At the same time demands fed by smaller pipes are aggregated and allocated to the nearest upstream node of a major pipe. Variable elimination is based on a mathematical formalism. A pipe network mathematical model is a system of simultaneous algebraic equations. Some of variables (flows and heads) can be eliminated from these equations using an algorithm, thus reducing the size of a model. Approximation is a method based on an estimation technique where an arbitrary topology of a simplified model is assumed, and subsequently the resistance of pipes is calculated by minimisation of an error function.

II.5.2 Simplified Oldham water supply model

The hydraulic model of Oldham water supply system has been simplified to 120 junction nodes and 112 pipes, while the reservoirs, water sources (WTW) and the active elements "pumps and active valves" have been kept in the model. Table II.13 shows the number of components in the full and simplified model of Oldham water supply system, while Figure II.14 depicts the simplified model.

Before starting to simplify the model, all permanently completely closed valves have been removed from the model, while all permanently fully opened valves have been replaced by pipes of the same hydraulic resistance.

Two reservoirs connected to the model via two permanently completely closed valves, “00014C31 and A00BAF15”, have been removed from the model, while the reservoir representing Buckton Castle WTW, “24800001”, has been replaced by source node.

Woodgate SR 1&2 are located on the inlet boundary of the Hawsewater Aqueduct, and have a water levels ranged from 144.6 to 145.7 m. These two reservoirs have been replaced by a fixed head reservoir of 145m.

Twenty nodes, one in the middle of each main trunk, have been selected to be kept in the simplified model to represent the leakage at the middle of the main.

Table II.13 Number of components in the full and simplified model.

Component	Full model	Simplified model	Comment
Junctions	3535	120	Extra nodes were kept to represent the term of pressure dependent leakage.
Reservoirs	5	2	2 reservoirs connected to the model through 2 permanently completely closed valves were removed from the model. 1 reservoir representing Buckton Castle WTW was replaced by source node.
Variable head reservoirs	12	10	Woodgate SR 1&2 were removed from the model.
Pipes	3279	112	
Pumps	19	12 pump group	The pump group has one or more of identical pumps
Valves	418	37	10 Reservoir feeder valves 7 Non-return valve 1 Pressure reducing valve 19 Normal control valve

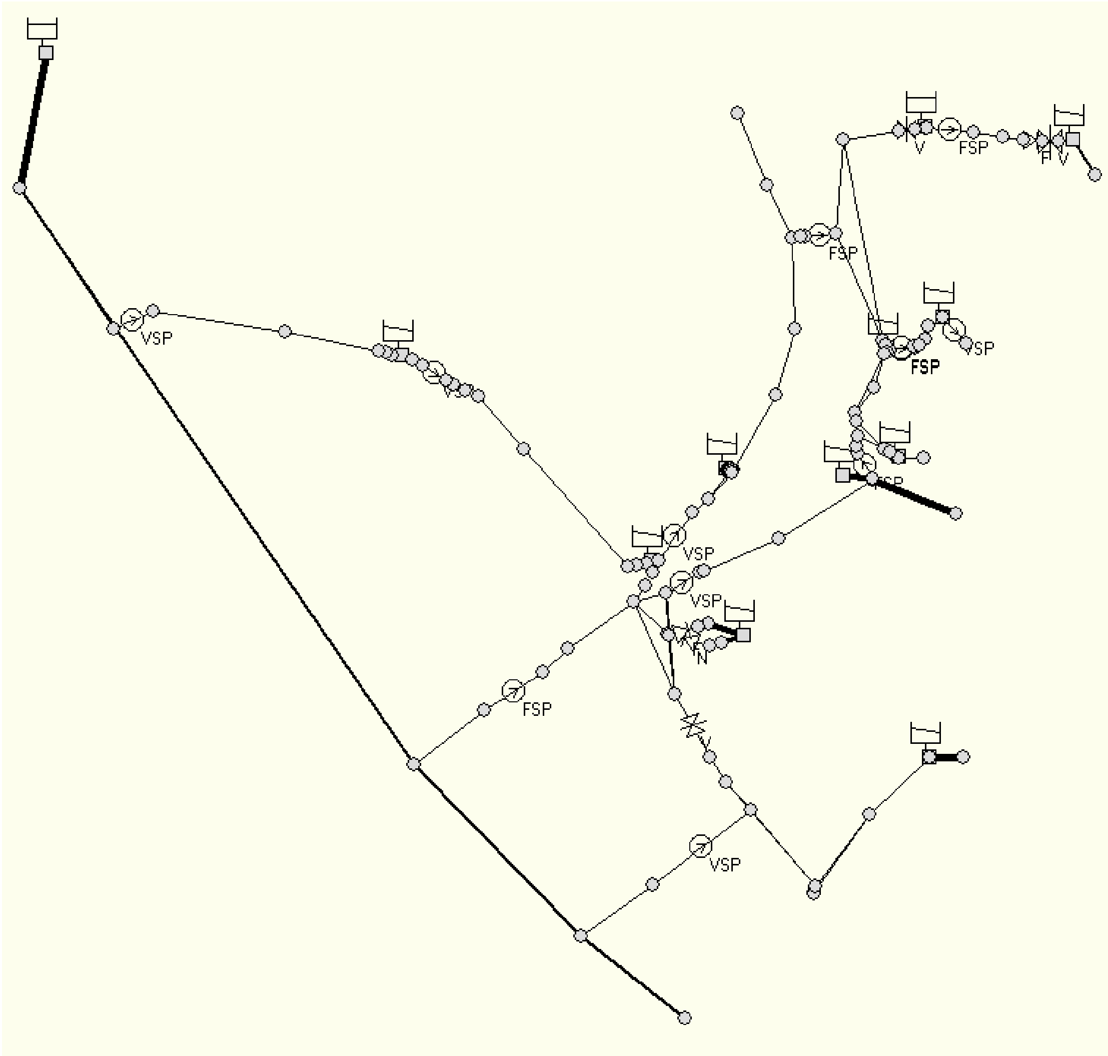


Figure II.14. the simplified model of Oldham water supply system

II.5.3 Verification of the simplified model

The simulation results of the simplified model of Oldham water supply system have been compared against the simulation results of the full model, in terms of pumps flow and reservoir trajectories. From the comparison, both models have the same hydraulic performances. Detailed results of simplified model verification are presented in (Abdelmeguid et al, 2009)[1]

[1] AbdelMeguid, H., Skworcow, P., and Ulanicki, B. (2009). "Energy and Pressure Management of Oldham Water Supply System - United Utilities case study "Off-line study"." Process Control - Water Software Systems, De Montfort University, Leicester, UK.

III Appendix C

The effect of changing the lower bounds of reservoirs constraints on the continuous solution.

In this study, the effect of changing the lower bounds of reservoirs constraints (LRCs) on the continuous solution has been tested using different LRC of 40 %, 55 % and 70 % of the full reservoirs water level and fixed initial reservoirs levels of 85 % of the full reservoir water level. The study has been conducted using 7 day scenario, and the pumps and the valve flows have been optimized only, while the WTWs flows have been taken from telemetry data (not optimised).

III.1 Continuous Pump Schedule at Different LRC

The figures below illustrate the pump controls, relative speed (for variable speed pumps) and flows from continuous solution for each pump station in Oldham water supply system at different LRCs.

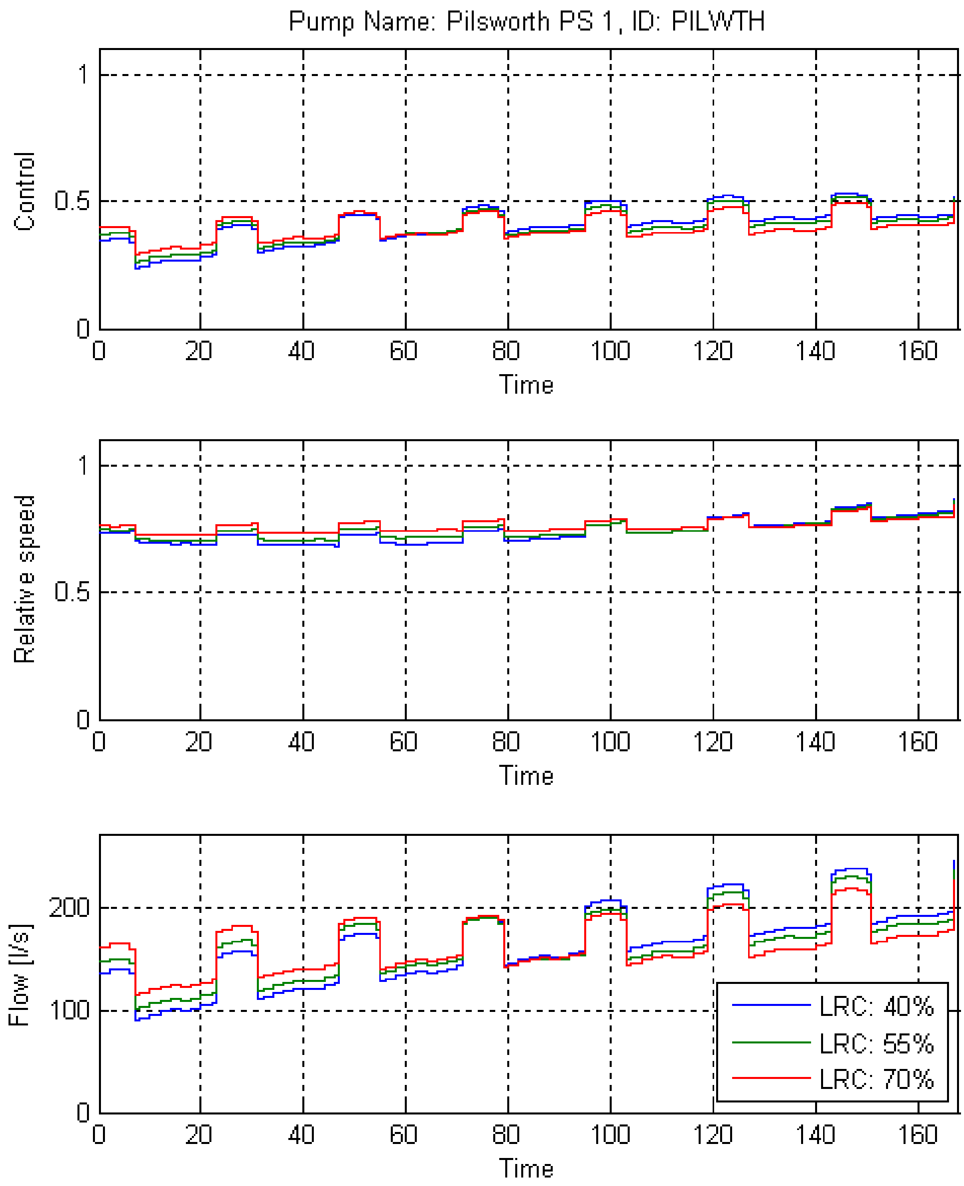


Figure III.1 Continuous pump schedule at different LRC for Pilsworth PS

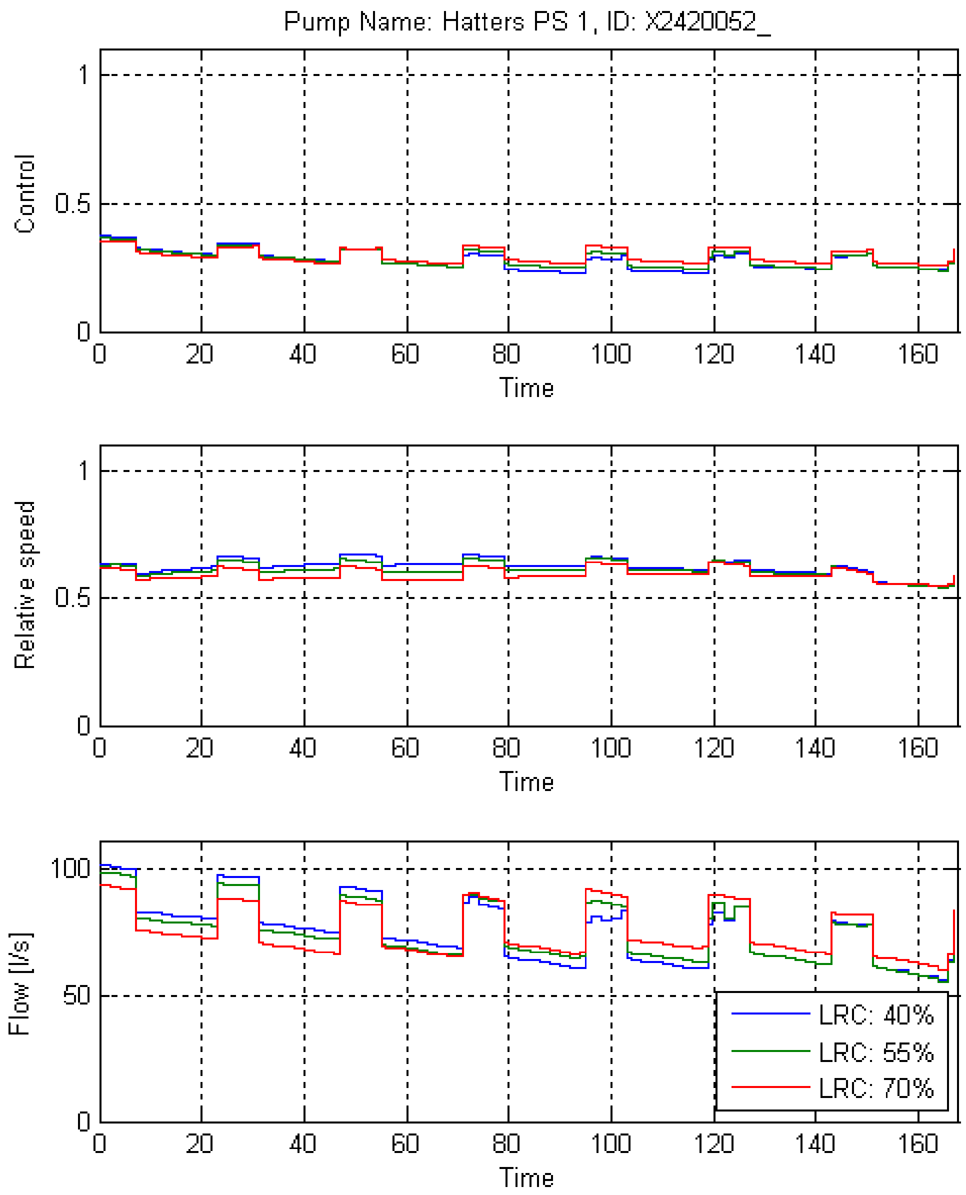


Figure III.2 Continuous pump schedule at different LRC for Hatters PS

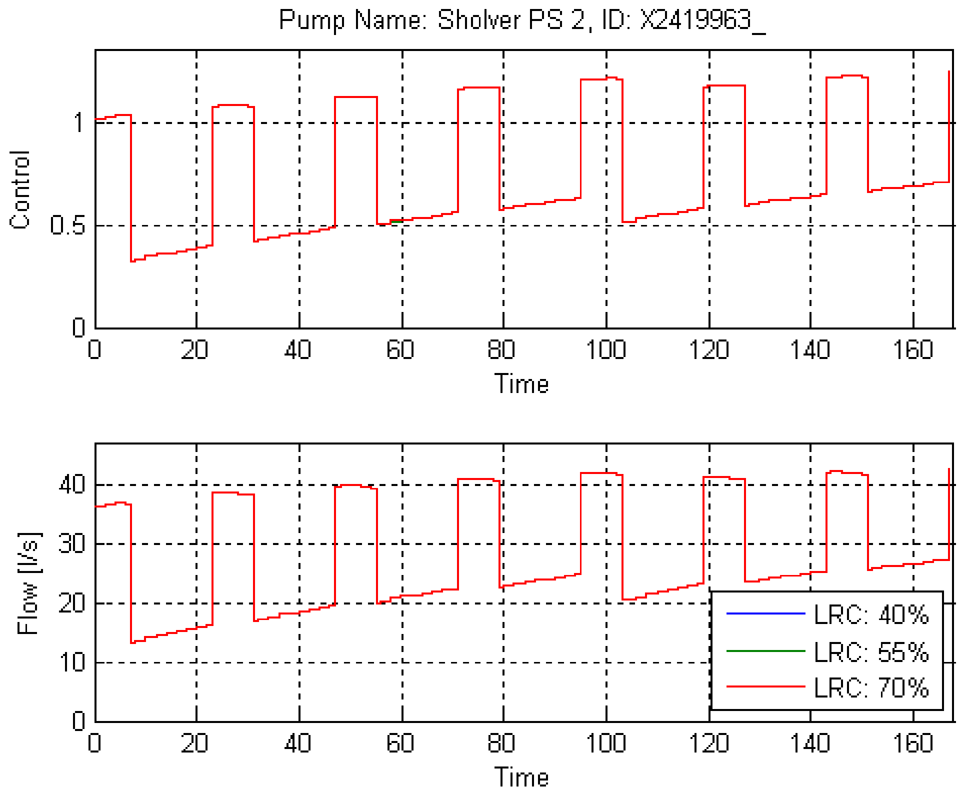


Figure III.3. Continuous pump schedule at different LRC for Sholver PS

III.2 Continuous Reservoir Trajectories at Different LRC

The figures below illustrate the reservoir trajectories from continuous solution for each pump station in Oldham water supply system at different LRCs.

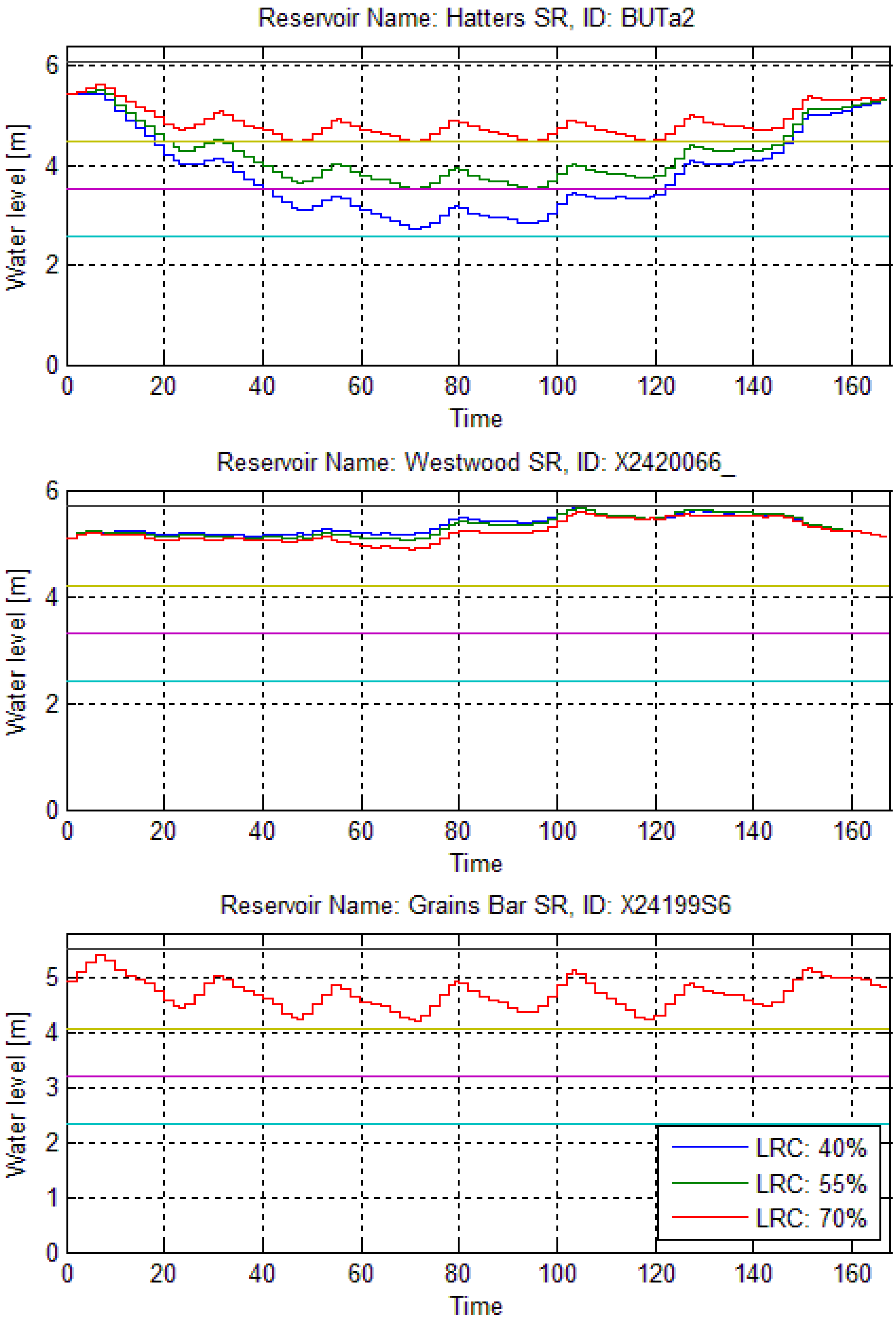


Figure III.4. Continuous reservoir trajectories at different LRC

III.3 Valve Flows of Continuous Schedule at Different LRC

The figures below illustrate the flows of Chapel Rd valve and Sholver-Counthill valve at different LRCs, the flows of these valves do not be affected by changing LRCs as depicted in the figures.

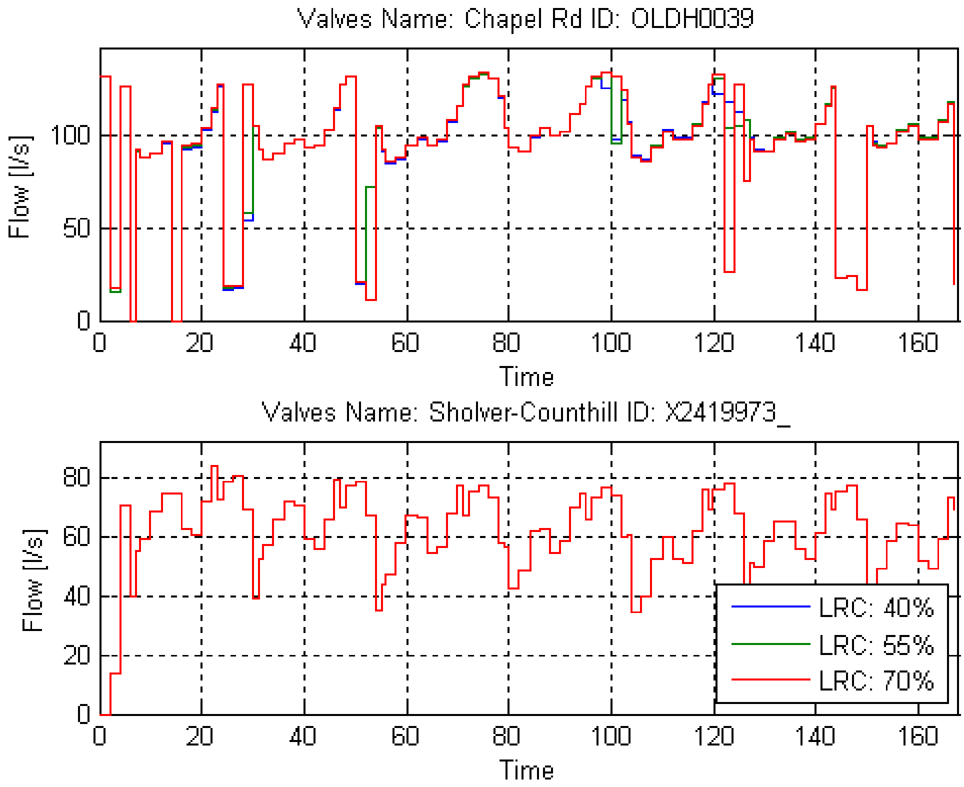
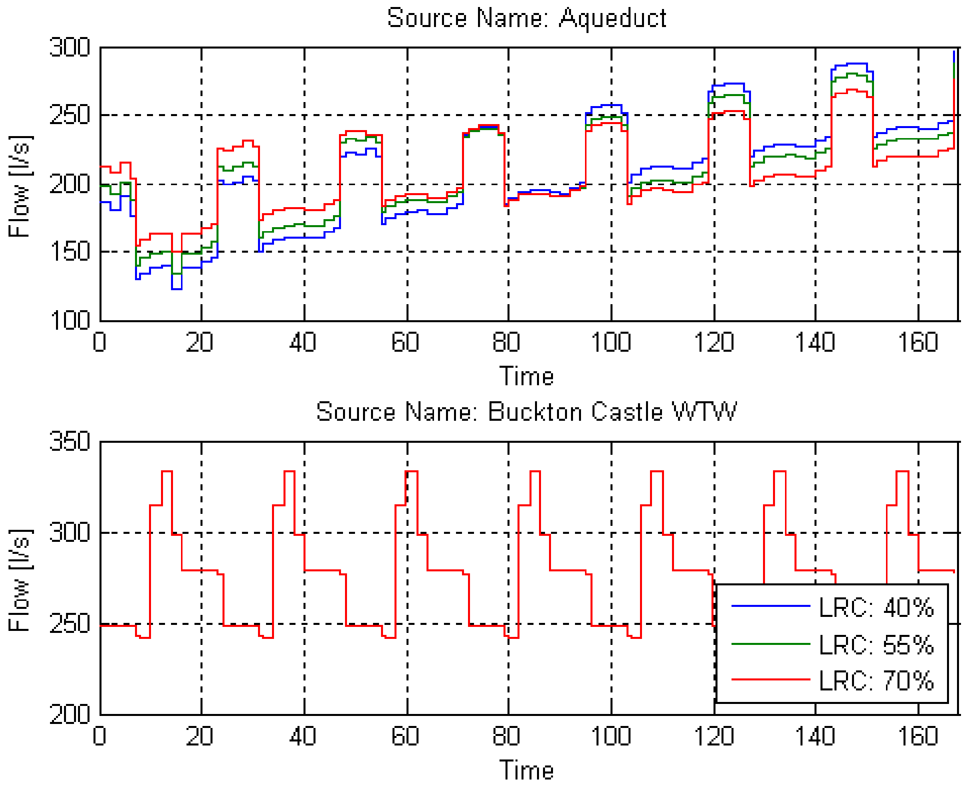


Figure III.5 Continuous valve schedule at different LRC

III.4 Sources Flow

The water flows from Piethorn WTW, Wickenhall WTW and Waterhead WTW are 184.6 l/s, 150.0 l/s and 133.50 l/s respectively and are constant all the time.



(a)

Figure III.6 Sources flows at different LRC

III.5 Summary

Changing the lower bound of reservoirs constraints (LRCs) have a minor impact on the continuous solution of the optimization problem. Only the Pilsworth PS and Hatters PS flows have slight differences, which affect the trajectory of Hatters reservoir.

IV Appendix D

Enclosed CD, file descriptions and paths.

IV.1 Models used in Chapter 5

1. Epanet model of E067-Waterside case study

   CDROM:\Chapter 5\E067-Waterside case study\Epanet Model\E057.INP

2. Finesse model of E067-Waterside case study

   CDROM:\Chapter 5\E067-Waterside case study\Finesse Model\e067.ntf

3. GAMS code of E067-Waterside case study

   CDROM:\Chapter 5\E067-Waterside case study\Gams Model_gams.gms

4. GAMS result file of E067-Waterside case study

   CDROM:\Chapter 5\E067-Waterside case study\Gams Model_gams.out

5. Epanet model of E093- Barrowby case study

   CDROM:\Chapter 5\E093- Barrowby case study\Epanet Model\E093.INP

6. Finesse model of E093- Barrowby case study

   CDROM:\Chapter 5\E093- Barrowby case study\Finesse Model\e093.ntf

7. GAMS code of E093- Barrowby case study

   CDROM:\Chapter 5\E093- Barrowby case study \Gams Model_gams.gms

8. GAMS result file of E093- Barrowby case study

   CDROM:\Chapter 5\E093- Barrowby case study \Gams Model_gams.out

IV.2 Models used in Chapter 6

1. Epanet model of A016 - case study

   CDROM:\Chapter 6\ A016 - case study\Epanet Model\A016.INP

2. Finesse model of A016 - case study

   CDROM:\Chapter 6\ A016 - case study\Finesse Model\a016.ntf

3. GAMS code of A016 - case study

   CDROM:\Chapter 6\ A016 - case study\Gams Model_gams.gms

4. GAMS result file of A016 - case study

   CDROM:\Chapter 6\ A016 - case study\Gams Model_gams.out

IV.3 Models used in Chapter 8

1. Epanet model of current operation of Oldham case study

   CDROM:\Chapter 8\Oldham case study\Epanet Model\ Oldham_Current.inp

2. Epanet model of optimized Oldham case study "case 3" using NLP

   CDROM:\Chapter 8\Oldham case study\Epanet Model\ Oldham_Optimized.inp

3. Finesse simplified model of Oldham case study "case 3"

   CDROM:\Chapter 8\Oldham case study\Finesse Model\oldham_s2_7days.ntf

4. GAMS code of Oldham case study "case 3"

   CDROM:\Chapter 8\Oldham case study\Gams Model_gams.gms

5. GAMS result file of Oldham case study "case 3"

   CDROM:\Chapter 8\Oldham case study\Gams Model_gams.out

IV.4 Models used in Chapter 9

1. Epanet model of current operation of Oldham case study

   CDROM:\Chapter 9\Oldham case study\Epanet Model\Oldham_Current.inp

2. Epanet model with derived optimal operational rules of Oldham case study

   CDROM:\Chapter 9\Oldham case study\Epanet Model\Oldham_GA.inp

3. Epanet model of optimized Oldham case study "case 3" using NLP

   CDROM:\Chapter 9\Oldham case study\Epanet Model\Oldham_NLP.inp

4. Finesse simplified model of Oldham case study "case 3"

   CDROM:\Chapter 9\Oldham case study\Finesse Model\ oldham_s2_7days.ntf

5. GAMS code of Oldham case study "case 3"

   CDROM:\Chapter 9\Oldham case study\Gams Model_gams.gms

6. GAMS result file of Oldham case study "case 3"

   CDROM:\Chapter 9\Oldham case study\Gams Model_gams.out