Optimization Approaches for Planning and Operation of Large-scale Water Distribution Networks

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Abstract

The aim of this thesis is to address two major issues in planning and operation of large scale water distribution systems (WDSs), which are operational pressure regulations to reduce leakage amount on the one hand and optimization of pumping energy and maintenance costs on the other hand. The optimal pressure regulation is achieved by optimal localization of pressure reducing valves (PRVs) and the operational optimization of PRVs is carried out to minimize the excessive pressure in water distribution systems while the minimization of pumping energy and maintenance costs is gained by optimal scheduling on/off operations of pumps. To effectively reduce the leakage flows in a WDS, this thesis proposes a new solution approach, namely, mathematical programs with complementarity constraints (MPCC), to solve the mixed integer nonlinear programming problem for optimal localization of PRVs. In addition, a new rounding scheme is developed to accelerate the solution procedure as well as improve the quality of the MPCC solution. The MPCC approach is then applied to optimal locations of PRVs for benchmark WDSs and the result reveals new optimal locations of PRVs, which results in higher decreases of leakage amounts and excessive pressures as compared with those found by the existing approaches. With water distribution systems where PRVs have already been installed, leakage reduction can be addressed by optimizing operations of PRVs. An extended model of PRVs is proposed in this thesis to describe a complete model of PRVs with three operation modes. This model, represented by a non-smooth equation, can circumstantiate many scenarios occurring in water distribution systems where the existing PRV model is not capable. Numerical experiments have shown that the extended PRV model outperforms the existing ones in terms of the quality and accuracy of the optimal solution.

Beside the pressure regulation to leakage reduction, this thesis also develops a general mixed-integer nonlinear programming (MINLP) approach for optimizing on/off operations of pumps in water supply systems with multiple reservoirs. A set of linear equality constraints is proposed to formulate the MINLP problem to effectively restrict the number of pump switches. As a result, the optimized pump scheduling leads at most to the specified maximum number of pump switches with reduced pumping energy costs. Furthermore, to optimize operations of large-scale WDSs, a software package is developed so as to automatically extract the optimization model from the simulation model in the EPANET environment and carry out the two-stage optimization approach to determine the optimal pump scheduling for a real and large-scale drinking water system. The software enables users to optimize operations of WDSs with a minimum effort.

Zusammenfassung

Das Ziel dieser Arbeit besteht darin, sich zwei Hauptaspekten bei der Planung und Betriebsführung von großen Wasserverteilungssystemen (WVS) zu widmen, die einerseits in der Druckregelung im laufenden Betrieb zur Wasserverlustreduzierung sowie andererseits in der Optimierung der Pumpenergie- und Wartungskosten bestehen. Die optimale Druckregelung wird durch die optimale Platzierung von Druckreduzierungsventilen (DRV) erreicht. Die Optimierung des Betriebs der DRVs wird durch die Minimierung des überschüssigen Drucks im Wasserverteilungssystem erreicht, während die Minimierung der Pumpenergie- und Wartungskosten durch die optimale Berechnung der Ein- und Ausschaltvorgänge der Pumpen erzielt wird.

Zur effektiven Wasserverlustreduzierung in einem WVS wird in dieser Arbeit ein neuer Lösungsansatz vorgeschlagen, nämlich ein mathematisches Optimierungsprogramm mit Komplementaritätsbeschränkungen (MOKB), um ein gemischt-ganzzahliges nichtlineares Optimierungsproblem zur optimalen Platzierung von DRVs zu lösen. Zusätzlich wurde ein neues Rundungsschema entwickelt, um sowohl die Lösungsprozedur zu beschleunigen als auch die Qualität der MOKB-Lösung zu verbessern. Der MOKB-Ansatz wurde danach auf die optimale Platzierung von DRVs für so genannte Benchmark-WVSs angewendet und brachte neue optimale Platzierungen von DRVs hervor. Diese Ergebnisse äußern sich in einer erhöhten Reduzierung von Verlustwassermengen und überschüssigen Drücken verglichen mit den Resultaten, die mit bisherigen Lösungsansätzen gefunden wurden.

In WVSs , in denen schon DRVs installiert worden sind, kann man die Wasserverlustreduzierung untersuchen, indem man den Betrieb der DRVs optimiert. Ein erweitertes Modell der DRVs wird in dieser Arbeit vorgeschlagen, in dem ein Gesamtmodell mit drei Betriebsmodi aufgestellt wird. Dieses Modell repräsentiert durch eine nichtlineare nicht-glatte Gleichung kann bei vielen Szenarios, die in WVSs auftreten, in die Details gehen, die mit existierenden DRV-Modellen nicht behandelbar sind. Numerische Untersuchungen haben gezeigt, dass das erweiterte DRV-Modell die existierenden Modelle in puncto Qualität und Genauigkeit der optimalen Lösung übertrifft.

Neben der Druckregelung zur Verlustreduzierung wurde in dieser Arbeit ebenfalls ein allgemeiner gemischt-ganzzahliger nichtlinearer Programmierungsansatz (GGNLP) zur Optimierung der Ein- und Ausschaltvorgänge von Pumpen in Wasserversorgungssystemen mit mehreren Speichern entwickelt. Eine Menge von linearen Gleichungsnebenbedingungen zur Formulierung des GGNLP und für eine effektive Beschränkung der An-

zahl von Ein-/Ausschaltungen wird vorgeschlagen. Als ein Ergebnis führt die optimale Berechnung höchstens zu einer spezifizierten maximalen Anzahl von Schaltvorgängen mit reduzierten Pumpenergiekosten.

Um darüber hinaus die Betriebsweise von großen WVSs zu optimieren, wurde ein Softwarepaket entwickelt, das automatisch das Optimierungsmodell aus einem Simulationsmodell aus der EPANET-Simulationsumgebung extrahiert und einen zweistufigen Optimierungsansatz ausführt, der den optimalen Pumpenbetrieb für ein real existierendes großes Trinkwasserversorgungssystem bestimmt. Die Software gestattet dem Nutzer die Optimierung der Betriebsführung von WVSs mit minimalem Aufwand.

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Nomenclature

Q	Link flow
$Q_{i,j}$	Flow on pipe ij
$\mathbf{Q}$	Vector of link flows
H	Nodal head
$\mathbf{H}$	Vector of nodal heads
h_p	Additional head of pumps
H_0	Shutoff head of pumps
γ	The specific weight of the liquid
p	Nodal pressure
P	Power consumption of pump
k	Iteration
x	continuous variables
y	Integer variables
A_p, B_p, C_p, D_p	Power coefficients of pumps
a_p, b_p, c_p	hydraulic coefficients of pumps
A_η, B_η, C_η, D_η	Efficiency coefficients of pumps
s	Relative speed of pump
Q_p	Flow of pump
n	Number of pumps in a pump station
η	Efficiency of pump
L	Pipe length
g	Acceleration of gravity
Re	Reynolds number
f	friction factor of Darcy-Weisbach equation
ϵ	the roughness of pipe
Δh	the head loss on pipe
K	Head loss coefficient

l_i	Leakage amount associated with node i
d_i	Demand associated with node i
V_i	Water volume of tank i
S_i	Cross-sectional area of tank i
h_i	Water level in tank i
Δt	Length of time interval
V	Average water velocity
H_{set}	The pressure setting of PRV
ν	Water viscosity
a, b, c, d	The parameters for the smoothed head loss
K_s	The slope of the smoothed head loss at Q=0.0
$\beta, \alpha, \gamma, z, f_k$	The parameters for the smoothed head loss
R_p	The parameters for the smoothed head loss
$\mathbf{G}$	The diagonal matrix with derivatives of head losses
$\mathbf{A}_{12}$	The connectivity matrix
$\mathbf{A}_{10}$	The connectivity matrix edge reservoir/tank node
$\mathbf{A}_{12}^T$	The transpose matrix of $\mathbf{A}_{12}$
$\mathbf{A}_{12}^T$	The transpose matrix of $\mathbf{A}_{12}$
$\mathbf{H}_0$	Column vectors of reservoir and tank heads
$\mathbf{A}_{11}$	The diagonal matrix with head losses dividing their flows
$\mathbf{x}$	a vector of continuous variable
$\mathbf{y}$	a vector of binary variable
f	The objective function
$g(x)$	Constraint
ρ	Penalty parameter
ε	The relaxation parameter
z^L, z^U	The lower and upper bounds of a MINLP
$M_{i,j}$	The big number associated with pipe i, j
H^M	Maximum head
N_p	Number of pipes in a WDS
N_n	Number of nodes in a WDS
N_L	Number of demand patterns
N_V	Number of PRVs
$v_{i,j}$, $v_{j,j}$	Binary variables in chapter 4

$v'_{i,j}$, $v'_{j,j}$	Binary values
θ	A predefined threshold value in chapter 4
z_{NLP}	Objective function value
z_{best}	The best objective function value found
μ	Penalty value in chapter 4
$R_{i,j}$	Resistance of PRV
$v_{i,j}$	A variable coefficient for a PRV in chapter 5
z_i	Binary variables in chapter 6
λ_i, λ'_i	the friction factors in chapter 6
N_{max}	Maximum number of pump switches
LU_i, LD_i	Minimum up and down times
n_p	Number of pump switches on in chapter 7
s_p	Relative speed of pumps in chapter 7
Δ_i	Allowable deficiency of the water tank level in chapter 7
Δ_p	Allowable change of pump station flows in chapter 7
TFL^d_{i,tp_i}	Total flow of pump station produced by the discrete pump scheduling
TFL^c_{i,tp_i}	Total flow of pump station produced by the continuous pump scheduling
k	Time step
k_d	Discretized time step in chapter 7
tp_i	Tariff time period
N_{tp}	Number of tariff time periods
Δt_{k_d}	Discretized tim interval
Δ_{tp}	Tolerance of flow deviation
$\widetilde{Q}_p$	Pump cutoff flow

Acronyms

NLP	Nonlinear programming
MINLP	Mixed integer nonlinear programming
LP	Linear programming
MILP	Mixed integer Linear programming
GA	Genetic algorithm
MPCC	Mathematical program with complementarity constraints
OA	Outer approximation
BB	Branch and bound
NCP	Nonlinear complementarity problem function
PRV	Pressure reducing valve
WDS	Water distribution system

Chapter 1

Problem statements

1.1 Optimal pump scheduling problem in water supply and distribution systems

Water is transported through the water network as shown in Fig. 1.1. The water network includes water supply and distribution systems. The task of a water supply system is to convey raw water (e.g., from a dam) to a water treatment plant where it is treated by various chemical and physical processes to guarantee the required quality standard. The treated water is stored in reservoirs that serve as water buffers to regulate the daily water demand. Water is delivered to customers and services through pipeline and pumping systems in a water distribution system. The significant amount of energy is associated with the pump operation to transport water in both water supply and distribution systems. Due to its dramatic price increases in the recent years, the electricity cost of pumping takes the most part of the total operating costs of water supply systems. In the United States, the energy consumption by pumping is 5% of all generated electricity [9] and similarly high amount of energy consumption in the European countries. Therefore, minimizing the energy costs while delivering water to meet customer demands is more and more important to water utilities

The pumping energy costs depend on the energy consumption and the energy rates (or electrical tariff). Energy rates are varied to encourage the energy usage in off- peak periods with lower rates whereas it penalizes the energy consumption in peak periods with higher rates [10]. To reduce the pumping energy consumption, many strategies have been taken such as pump testing, replacing or repairing inefficient pumps, modifying the pump characteristics to match the system, and selecting the best pumps for the application [11]. One of the most effective approaches for reducing the energy consumption is optimal scheduling of the pump operations [12].

The aim of optimal pump scheduling is to determine on/off operations of pumps in order to reduce the pumping energy cost while fulfilling the physical and operational constraints [13]. Although the optimal pump scheduling is highly desirable, it leads to a

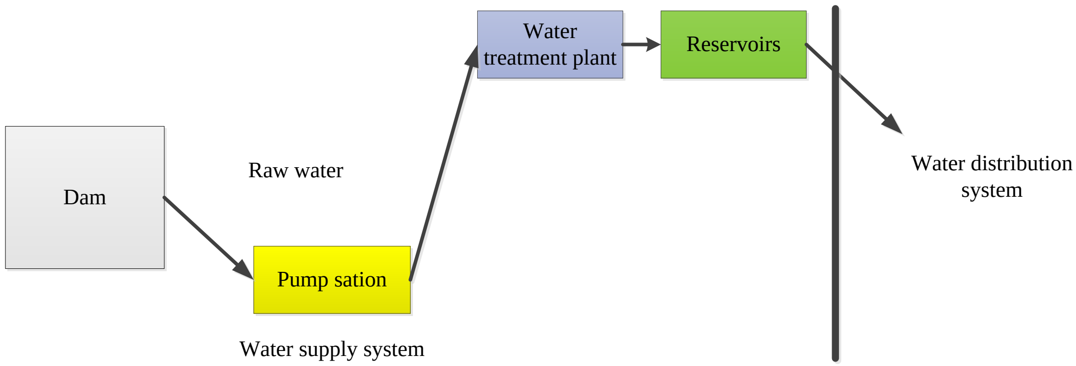


Figure 1.1: A water network [3]

very difficult mixed integer nonlinear optimization problem, since binary variables have to be introduced to represent the on/off operations of the pumps [3, 14]. In addition, an optimal pump scheduling in which pumps are switched on and off many times may reduce the pumping energy cost significantly, but it may increase the wear and tear on the pumps and thus the resulting pump maintenance and repair costs [15]. By restricting the number of on/off pump switches in the operation of pumps, the maintenance and repair costs can be decreased [15]. To solve the mixed integer nonlinear optimization problem (MINLP) for optimal pump scheduling in water supply and distribution systems, many optimization algorithms have been developed such as: linear programing (LP) [16, 17], mixed integer nonlinear programming (MINLP) [18, 19], dynamic programing (DP) [15], and heuristic algorithms [20].

1.2 Pressure regulating problem in water distribution systems

Water loss occurs in all water distribution systems (WDSs) [21] due to many reasons, from physical network to operation policies (e.g., a WDS operate with high pressure). For this reason, reducing and controlling water loss is very important to water utilities worldwide, especially in the age of rapidly growing demands and scarcity of the water resources. The non-revenue water (NRW) in many Asian cites reaches to 46% of total demand in which the real loss is as high as 75% [10, 22]. In European Union (EU) countries, the average water loss level is about 20% of the treated drinking water. The average yearly water loss in Turkish cities is as high as 51% of the total water production [23, 24]. In City of Mutare in Zimbabwe, the average water loss is about 57% [25]. Leakage is not only an economical issue for water utilities, but it is also an environmental, sustainability and potentially a health and safety issue [26, 27]. Leakage leads the energy for pumping water to be wasted and it may cause a serious effect

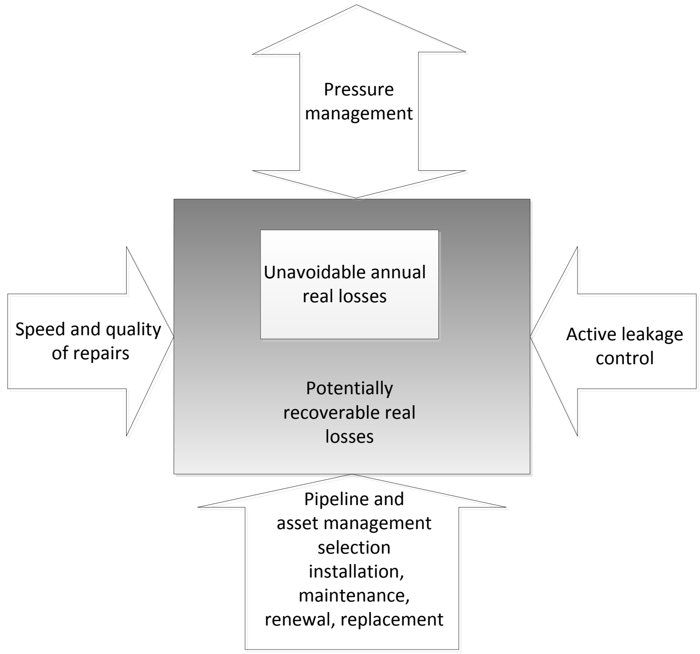


Figure 1.2: The four primary methods of controlling water losses (IWA water loss task force and AWWA Water loss control committee)

on water quality since toxic materials and chemicals can inject into water systems through leak hotspots or pipe breaks and bursts in low pressure conditions. Water loss is defined as a total loss and equals to real losses and apparent losses from a network. Real losses include leakage from pipes, seepage from joints, fittings, pipe bursts, and from services, tank over flows. Real losses can exist for months, or even years [10] due to undetected leak hotspots or bursts. The quantity of the water loss depends on the network characteristics (i.e., length of mains, number of service connections, length and material of the supply pipe) and operating parameters such as system pressures and leakage detection/ repair activities. In contrast to real losses, the apparent loss is due to illegal uses of water and metering inaccuracy.

To reduce the water loss, four primary approaches, shown in Fig. 1.2, are proposed by the Water Losses Task Force of IWA. They are *pipeline assessment management*, *speed and quality of repairs*, *active leakage control*, and *pressure management*. The yearly number of new leaks is influenced primarily by long term pipeline rehabilitation and management. The speed and quality of repairs determine the average duration of leaks lasts, while the active leakage control strategy involves in detecting or locating unreported leaks. Pressure management has a significant influence on the reduction of new leaks, and the flow rates of all leaks and bursts. Experimental data has indicated that the leakage flow at a node is proportional to a power function of the pressure at this node, with the exponent ranging from 1.15 to 1.18 [28, 29]. Therefore, pressure management is considered as a cost- effective means of reducing leakage [30]. Basically, the higher the system pressure is, the larger the leakage flow appears in the system and vice versa [27].

Pressure management to leakage reduction in a water distribution system can be achieved by optimizing *locations* and *operations* of pressure reducing valves. This leads to a mixed integer nonlinear optimization problem and a nonlinear optimization problem, respectively. Many algorithms have been developed to solve the two corresponding optimization problems such as Genetic algorithms (GAs) [31], multi-objective optimization (MOGA) [32], Scatter search [33], evolutionary algorithms [34], mixed-integer nonlinear programming (MINLP) [35, 36], and nonlinear programing (NLP) [37].

1.3 Motivation of the research

The overall motivation of the research of this thesis is to develop efficient solution approaches for solving the optimal pressure management to reduce leakage in water distribution systems and the optimal pump scheduling to reduce pumping energy and maintenance costs in water supply and distribution systems

1.3.1 Pressure management to leakage reduction

Optimal localization of pressure reducing valves (PRVs) to minimize the leakage flows in WDSs is formulated as a mixed integer nonlinear program (MINLP), since the binary variables are introduced in the optimization problem to identify whether or not. PRVs are placed on links. For large scale water distribution systems, this leads to a large-scale MINLP with a large number of binary variables [35, 36]. In addition, locations of PRVs should be accounted for multiple demand scenarios and leakage at nodes should be considered to represent realistic operations of WDSs. These two issues make the MINLP problem more complicated and thus not easily to be solved by available MINLP solvers. Meta-heuristic algorithms have been applied to solve such MINLP problems such as: Genetic algorithms, scatter search, multi-objective optimization etc. Although the meta-heuristic algorithms are suitable to deal with both binary and continuous variables, they sometimes cannot locate highly accurate solutions and may produce only suboptimal solutions [38]. Moreover, they require a large number of objective and constraint function evaluations, and hence are inefficient for solving large-scale MINLP problems [38]. For this reason, *it is essential to develop an efficient approach to optimal localization of PRVs*. Mathematical program with complementarity constraints (MPCC) is a promising solution approach to a certain class of MINLP problems [39], however it has not been investigated yet to address the optimal localization of PRVs in WDSs. This motivates the research of this thesis to further develop a general approach of MPCC to solve the optimal localization of PRVs in WDSs.

MPCC solution strategy is implemented by solving a sequence of NLP problems in which the relaxed complementarity constraints are gradually tightened or the penalty coefficients are gradually increased [40, 41]. The successive solutions of NLPs, called stationary points, will converge to a final solution (or limit point). It is due to the fact that the NLP solutions depend on their initial guesses and MPCC parameters like penalty coefficients or relaxed parameters, there may be several limit points of MPCC. These limit points could be undesired local solutions of the MINLP. Therefore, the MPCC solution approach should be improved to avoid such local solutions. In this thesis, a novel rounding scheme is proposed to improve the effectiveness of the MPCC solution approach.

For water distribution systems where PRVs have been already installed, leakage reduction can be attained by optimal control operations of the PRVs. To effectively reduce leakage, a fast and efficient method to calculate optimal PRV pressure settings is necessary [42]. Optimal operations of PRVs can be achieved by model based optimization and one of the fast optimization approaches to solve such an optimization problem is the nonlinear programming method [42]. The head- flow relation for describing pipeline hydraulics and PRVs represents the most important part in the optimization model. However, the model for PRVs having been using until now for optimal regulation using nonlinear programming methods is a two-mode model [37, 42] which cannot circumstantiate many situations in WDSs where the PRVs can operate as a check valve to prevent reverse flows. Therefore, *an extended model representing full operation modes of PRVs is developed* in this thesis. Numerical experiments are carried out to demonstrate the advantage of the extended model.

1.3.2 Optimal pump scheduling to pumping energy and maintenance cost reduction

For water supply systems, demands are lumped at reservoirs, and pumps convey water directly to reservoirs. For these reasons, the mass balance hydraulic model representing linear relationships between flows coming in and out of reservoirs and their heads is widely used in the formulation of the optimization problem [3, 19]. The pumping energy cost is commonly represented by a nonlinear function. Pumps operating with excessive pump switches will increase the maintenance and repair costs. Thus an optimal pumping schedule should consider the pumping energy cost and the number of pump switches. Therefore, in this work a constraint to restrict pump switching is introduced in the optimization problem. However, such a constraint is described by a non-smooth function, and thus, it cannot be used in the formulation of MINLP or MILP. An efficient approach for handling the number of pump switches is developed in this thesis which allows the formulated the MINLP problem to be solved by MINLP algorithms while does not increase the complexity of the MINLP problem by retaining the linear constraints. In this way, the limitation on number of the pump switches can be carried out by constraints restricting the total number of pump switches or restricting the on/off time periods of pumps.

In contrast to water supply systems, demands are distributed in water distribution systems, and the relationships between the elements in WDSs are nonlinear and non-convex. Thus the resulting optimization problem is a nonlinear and non-convex mixed integer nonlinear programming (MINLP). It is difficult for existing MINLP solvers to solve such MINLP problems, especially MINLP problems for large-scale WDSs [8, 43]. Genetic algorithms are well suited to solve such optimization problems. However, it requires a large amount of computation time and hence cannot be employed for online optimization of large - scale water distribution systems. Therefore, a systematic and fast solution approach should be developed. In this thesis, a two-stage optimization is proposed to determine optimal pump scheduling for a real and large scale WDS. The first optimization stage will determine the continuous flow set-points for pump stations while the on/off operations of pumps in each pump station will be deduced in the second optimization stage to approximate the continuous flow set-points using a simple heuristic algorithm.

1.4 Contributions of the thesis

The contributions of this thesis can be summarized as follows:

1. A numerical approach to mathematical program with complementarity constraints (MPCC) for solving the optimal localization of pressure reducing valves (PRV) in WDSs is developed. Moreover, a novel rounding scheme is proposed to accelerate the solution procedure as well as the quality of the MPCC solution. The optimal results reveal new locations and combinations of PRVs, which result in a higher decrease of leakage amount and excessive pressure as compared with those (PRV locations) reported in the literature. The contribution is presented in chapter 4 and published in [36].

2. An extended PRV model, which can circumstantiate three operation modes of pressure reducing valves (PRVs), is proposed. The model is shown to be more accurate than the existing one in optimal pressure regulations in WDSs. In fact, the use of three mode model of PRVs will result in lower leakage amount and excessive pressure as compared with the use of the existing PRV model. The contribution is given in chapter 5 and submitted for publication in [44].

3. For handling the number of pump switches in optimization of pumping energy and maintenance costs a set of linear equality constraints instead of the non-smooth one is proposed. This allows the use of MINLP solvers for solving the optimization problem. The optimized pump scheduling reduces the pumping energy cost and meanwhile leads to a user-defined number of pump switches. The contribution is presented in chapter 6 and published in [45].

4. An application of a two-stage optimization approach to optimize the operation of a real and large-scale drinking water network is carried out. In addition, a software

package is developed to extract the optimization models from simulation models in the EPANET environment. This will significantly relive the burdens as well as avoid prune errors in formulating the optimization problem. The contribution is presented in chapter 7.

1.5 Structure of the thesis

The structure of this thesis including chapters is shown in Fig. 1.3

Chapter 2 presents the state-of-the-art about three following research areas in water distribution systems (WDSs): 1) the optimization approaches to identify optimal localization of pressure reducing valves (PRVs) to minimize excessive pressure in WDSs, 2) the optimization approaches and model of PRVs to optimize the operation of PRVs for leakage reduction in WDSs, and 3) the optimization approach to optimize the pumping energy and maintenance costs in water supply and distribution systems.

Chapter 3 introduces the modeling of water distribution systems. In addition, optimization algorithms used in this thesis such as the mathematical program with complementarity constraints (MPCC), nonlinear programming (NLP), and MINLP algorithms are briefly presented.

In *Chapter 4* an optimal localization approach for pressure reducing valves to minimize the excessive pressure in a WDS is developed. The optimal localization is formulated as a MINLP problem and the mathematical program with complementary constraint (MPCC) approach is applied to solve it. In addition, a novel rounding scheme is proposed to improve the MPCC solution approach.

Chapter 5 presents an extended model of PRVs. This model is applied in optimal pressure regulation in WDSs. In addition, comparisons between the extended PRV model and the existing ones is carried out by considering optimal pressure regulations in WDSs with different demand scenarios.

In *Chapter 6* an optimization approach for energy and maintenance costs in water supply system with multiple reservoirs is proposed. This approach employs a set of linear equality constraints instead of using the non-smooth constraints for handling the number of pump switches and hence the maintenance cost. As a result, the desired number of pump switches can be accomplished by constraints regulating the total number of pump switches or regulating the on/off time periods for each pump.

Chapter 7 presents an operational optimization of water distribution systems based on a two-stage optimization approach. In the first optimization stage, a continuous NLP problem is formulated and solved to determine optimal flow set-points for pump stations. The discrete (on/off) operations of pumps in pump stations will be deduced in the second optimization stage to approximate the optimal continuous flows. This approach is applied to solve the operational optimization of a real and large-scale drinking water network.

Finally, conclusions of this work and future research aspects are given in *Chapter 8*.

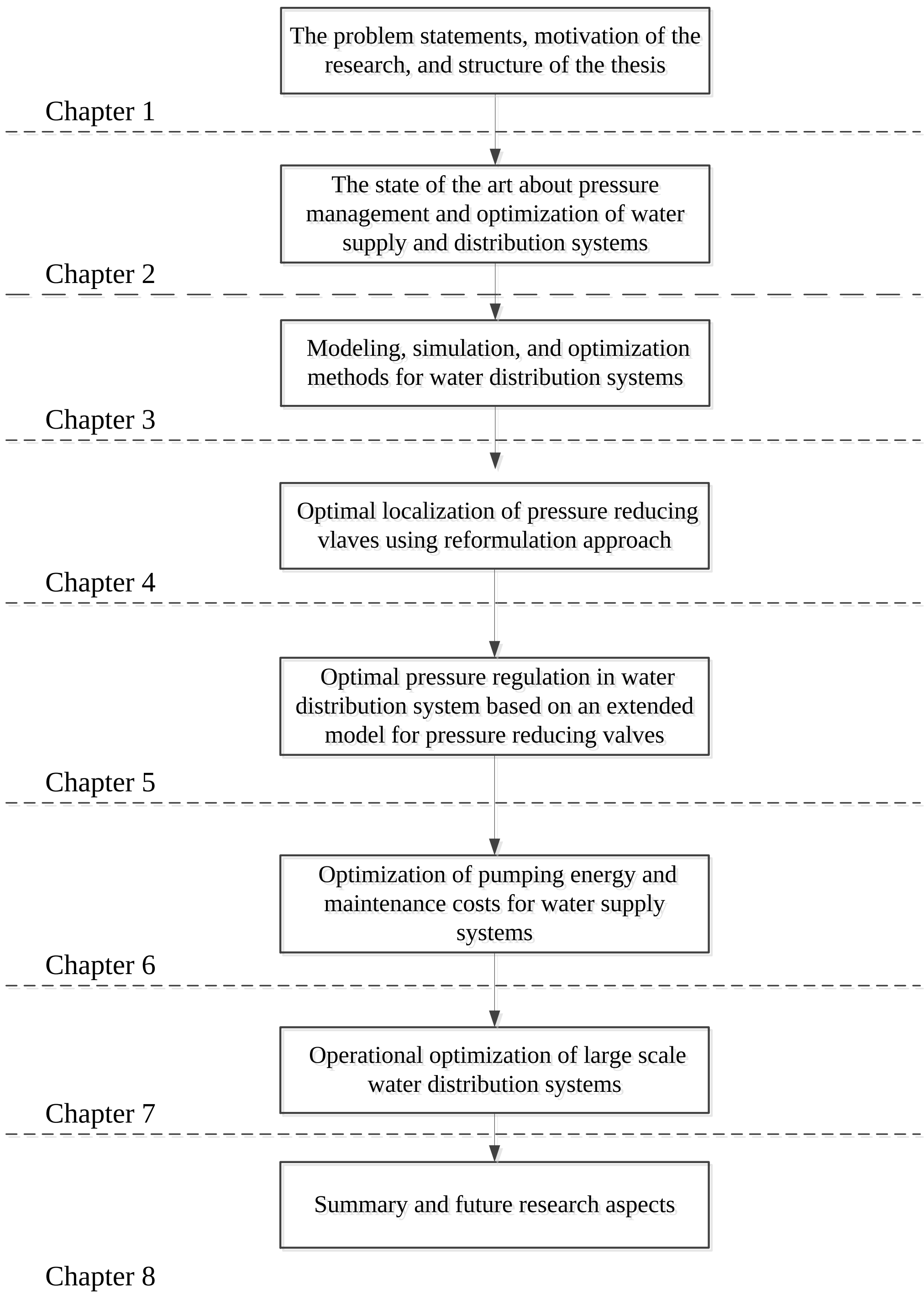


Figure 1.3: Structure of the thesis

Chapter 2

The state of the art

2.1 Optimal localizations of pressure reducing valves in Water distribution systems

It is a commonly recognized fact that the water loss in water distribution systems takes a large part of the total supplied volume[1, 21, 32]. Water losses are generally classified into apparent and real losses [21, 46]. The apparent loss is due to inaccurate meters and/or unauthorized consumption, whereas the real loss is caused by leakages at network fittings, pipe joints, breaks and/or bursts in pipes. To reduce leakages in water distribution systems many strategies have been proposed ranging from pipe rehabilitation, detection and reparation of existing leaks to operational pressure management [30, 32]. Water leakages can be considered as additional demands at nodes and mathematically modeled as a proportional relation to the nodal pressures [30, 47]. The amount of water losses increases significantly as the average system pressure rises [48]. For this reason, it is desired to decrease system pressures in order to reduce water losses [48]. In addition, due to the decreased operating pressure, the risk of further leaks and incidences of pipe bursts can be avoided or limited [21, 30].

The placement of PRVs and regulation of system pressures are considered as major tasks for operational pressure management [1, 31, 32, 33, 35, 48]. To formulate the localization problem, a binary variable for each link has to be introduced to represent the valve placement (i.e., 1 means a valve is present and 0 not present on the link). Therefore, the localization task leads to a MINLP problem with a large number of integer (binary) variables which usually cannot be easily solved directly by an existing MINLP software package [49, 50]. Moreover, to achieve a robust decision for the valve placement, multiple demand scenarios ought to be included which makes the problem formulation even more difficult to solve.

There are many optimization methods which have been applied to address the optimal location of PRVs. They can be classified into mixed integer linear programming (MILP), mixed integer nonlinear programming (MINLP), and meta-heuristic algorithms (e.g., genetic algorithm, scatter search, evolutionary algorithm, etc).

2.1.1 Mixed integer linear programming

The localization of control valves was first considered in [51] for pressure reduction. The authors proposed a method to select pipes where control valves can be placed so as to minimize both the pressure and the capital cost of installing valves by one objective function. The optimization problem is formulated as a mixed integer nonlinear programming (MINLP) in which binary variables are introduced to represent locations and types of control valves. It was then approximated to a mixed-integer linear program (MILP) by separable linearization of nonlinear equations. The solution approach applied to localization of control valves for a network with 15 nodes and 21 pipes demonstrates a good computational efficiency.

Although MILP problem can be solved efficiently using branch and bound search, a shortcoming of this approach is that the linearized model for large scale WDSs (e.g., a WDS has thousands of pipes and nodes) leads to a low accuracy which may cause an infeasible solution.

2.1.2 Mixed integer nonlinear programming

More recently, optimal localization of PRVs is formulated as a MINLP problem [35] in which binary variables represent locations of PRVs on links in bidirectional flows. Using this approach, the computation time for solving a small MINLP problem with 74 binary variables was 555 seconds and it took over 150 hours for solving a large one with 4926 binary variables [35]. Although this formulation of MINLP is general and can be applied to any water distribution systems, leakage at nodes and multiple demand patterns were not considered in the approach. To represent real water system operations leakage should be considered in the formulation of MINLP. Moreover, it is critical to consider multiple demand patterns so that the locations of PRVs account for all operating scenarios. Adding these two major issues in the problem formulation makes the MINLP problem more difficult to solve since the number of continuous variables increase dramatically.

2.1.3 Meta-heuristic algorithms

Under one demand scenario, Savic and Walters. 1996 addressed the localization problem by considering only on and off states of isolating valves as binary variables [34, 48]. They employed an evolution program (EP) to search for optimal valve locations to minimize the average excessive pressure. The EP is coupled with a hydraulic solver which uses a method based loop equations, namely, the linear theory method to accelerate the search of EP.

Reis et al in [31] also used GA combined with a linear theory method to optimize control valve locations for minimizing leakages under different demand, the number of control valves, and reservoir levels. While the GA procedure identifies optimal locations of control valves, the linear theory method [7, 52] determines the optimal valve settings for these corresponding valve combinations and calculate the objective function value. To evaluate the efficiency of the solution approach, the optimal control valve location for a benchmark WDS with 37 pipes and 25 nodes in [7] is considered. The results showed that a considerable leakage amount can be reduced even with a few valves when they are located optimally. Moreover, it was shown that the leakage in the system is relatively insensitive to changes of the demands and reservoir levels.

In [53], a GA solution approach was used to solve the optimal locations of PRVs for a real WDS in the city of Mahalat in Iran. Two objective functions are defined including the maximization of the number of nodes having appropriate pressures and the minimization of leakage flows in a WDS. The results showed that both optimal solutions result in higher leakage decrease and a higher number of nodes with appropriate pressure as compared with the solution suggested by the expert choice. In addition, there are no correlations between the optimal solutions obtained from the two objective functions.

It is due to the fact that a WDS can have thousands of pipes, and if all pipes are considered as potential locations for PRVs, the search space will be very large. A GA based two-phase method was proposed by Ajauro et al. in [1] to solve the pressure management problem. In the first phase, the number of possible valves in the network was determined. In the second phase, the combinations of the possible valves were considered based on their frequency appearance and then the valve openings were determined so that a compromise between the leakage reduction and the number of valves can be gained. Also, a two-phase optimization approach based scatter search was also used by Liberatore and Sechi. 2007 in [33]. In the first phase, the pressure reference method [33] was used to limit PRV locations into a set of limited pipes. Due to the approach, the links were considered as candidates if they connect two nodes in which one node has a pressure exceeding the reference pressure. In the second phase, a scatter search algorithm was employed to calibrate the valve openings under multiple demand scenarios. Since the search space was limited to the reduced link candidates, the computation time could be considerably decreased. However, only a limited set of link candidates, determined based on the mean demand in the first phase, were used in the second phase for the search space which may not cover the optimal solution.

Using the same idea to limit locations of PRVs to a set of potential pipes, significant indexes (SI) for pipes in WDSs were introduced in [54] to indicates the relative importance of a pipe over the others. The pipe with a higher value of SI will have more impact on the water distribution system than the others with lower values of SI. The pipes are then arranged due to their SI values. Only a certain number of pipes among these pipes (i.e., 60%) are chosen as potential locations for PRVs [54]. Similar to the approaches in [1] and [33], the use of SI will eliminate inefficient solutions for PRV locating problems and, more importantly, it reduces the search space for Genetic Algorithms. As a result, the computation time for GA solution can be significantly reduced. However, the number of potential links for PRV locations was estimated for the mean demand in that study, which may not cover the best combinations of PRVs.

To reduce computation time required by GA approaches for solving PRV locating problems, a hybrid approach (LLHA) was proposed in [55]. In this approach, optimal openings of control valves is solved using iterative linear programming while the optimal locations of control valves and on/off operations of isolated valves are determined by a multi-objective optimization (NSGA II) to minimize two objective functions: daily leakage volume and the cost of installing control valves. The results demonstrated that the hybrid approach achieves higher computational efficiency as compared with the use of NSGA II. In [32], Nicolini and Zovatto. 2009 proposed to use a multi-objective GA (NSGA II) to optimize both the number of PRVs installed and their locations under multiple demand scenarios. As a result, a Pareto set of optimal solutions was achieved, leading to a trade-off between the number of valves installed and the amount of water leakages.

For design of water distribution systems, the authors in [29] addressed the design of pipelines in a water distribution system simultaneously with determining optimal locations of PRVs. A combined solution approach, namely, Genetic algorithm combined with a nonlinear programming algorithm, is used to solve the optimization problem. In this approach, the GA procedure is used to choose optimal diameters of pipes and identifies optimal locations of PRVs, while a nonlinear programming solver is used to determine the optimal valve settings.

Although meta-heuristic algorithms are suitable to deal with both binary and continuous variables, they sometimes cannot locate highly accurate solutions and may produce only suboptimal solutions, In addition, they require a large number of objective and constraint function evaluations, and hence are inefficient for solving large scale optimization problems [38].

2.2 Optimal operations of pressure reducing valves in Water distribution system

The leakage amount in a WDS increases significantly when operating at an excessive pressure [48]. For this reason, reducing the excessive pressure will lead to a reduction of the leakage amount and the risk of further leaks in a WDS [30, 47, 48]. The leakage reduction problem can be accomplished by a model-based optimization aiming at optimal regulations (or schedules) of the pressure reducing valves (PRVs) and/or the isolated valves in WDSs. [7, 37, 42]. For the isolated valves the optimization task is to determine their on/off operations [34], while for the PRVs their pressure settings (openings) is to be determined by the optimization [37]. The minimization of excessive pressure by optimal operations of PRVs and/or isolated valves can be achieved by formulating and solving a nonlinear programming (NLP) problem [37, 42] and/or a mixed-integer nonlinear programming (MINLP) problem [34], respectively.

2.2.1 Successive linear programming

The method of successive linear programming [6, 7, 47] was used to solve the NLP problem where the objective function was defined as the sum of differences between each nodal pressure and the minimum allowable pressure. It was an iterative approach that involves a linearization of the objective function and the constraints around the current solution and then a LP problem is solved to obtain the new solution. The procedure is repeated until a convergence criterion is satisfied. In particular, the authors in [7, 47] used the linear theory method [52] to linearize the nonlinear equations of the optimization problem and then the linear programming problem is solved to obtain the new solution. In [6], the authors used the Newton-Raphson method to linearize the nonlinear equations and then a LP was solved to calculate the quantities for updating the current solution to the new one.

2.2.2 Nonlinear Programming

In [37] the authors formulated a NLP problem for optimal pressure regulation to minimize the leakage flow in WDSs, in which the nodal pressures are allowed to be lower than their minimum values by a minor violation in order to achieve a higher decrease of leakage amount in a WDS. Two different objective functions were used: 1) the sum of excessive pressures and 2) the sum of available leakages. It was shown that the use of the first option will lead to a higher reduction of leakage amount as compared with the use of the second option. In [56] the authors used parallel computing technology to accelerate the minimization of leakage flows in water distribution systems. The optimization problem to determine PRV pressure settings was carried out for a time horizon of 24 hours. It is due to the fact that sub NLP problems are independent, so parallel computation can be implemented. In fact, the sub NLP problems were organized by a master processor and solved by slave processors. Numerical results have shown that using the approach, the leakage flow decreases significantly and the computation time is reduced.

Ulanicki et al. in [30] proposed an on-line control strategy for pressure regulations in the Domestic Metter Areas (DMAs). Two control schemes for PRVs were proposed: predictive control and feedback control. In the first scheme, the model of network and demand was hourly updated and hourly PRV set points were calculated by a NLP method. On contrary to the predictive scheme, the feedback control scheme instead requires the model and demand updated hourly, it optimizes the PRV set points for a certain number of demand patterns (e.g., 24 demand patterns). The relationships between optimal outlet pressures (or pressure settings) and flows of PRVs were constructed for PRV controllers. The controllers continuously adjusted the pressure settings for the PRVs due to measurements of flows at the outlet of the PRVs. The feedback schedule scheme, if possible, was valid for a wide range of demands and did not require re-calculation when the demand changes. Therefore, it is suitable for on-line regulations of PRVs. Ulanicki et al. in [42] presented an approach to optimize the schedules of both boundary and internal PRVs for 24 hours to minimize the leakage flows in DMAs. The nonlinear optimization problem was formulated and solved by the CONOPT solver [57]. As a result, the control flow modulation curves for PRVs, i.e., the relations between the flows and the pressure settings which are essential for online PRV control, were deduced.

2.2.3 Meta-heuristic algorithms

Savic and Walters in [34] optimized the on/off operations of isolated valves to minimize the excessive pressure in a WDS using an evolutionary algorithm. Genetic algorithms combined with EPANET 2 [58] were also used to determine optimal outlet pressures of PRVs for pressure regulations in WDSs [53, 59, 60]. From the optimal solution, the outlet pressures of a PRV can be calculated hourly using time schedule [42, 59] or adjusted continuously using flow modulating schedule [60].

In [60], the authors developed the flow modulation curves for PRV controllers using a genetic algorithm. The pressure control in a district metering area was formulated as a NLP problem in which constraints relating to PRV pressure settings and their flows by second order curves with unknown coefficients were introduced. The unknown coefficients for the modulation curves of PRVs are decision variables and determined by solving the optimization problem using GA. Numerical experiments have shown that the resulting modulation curves operate robustly over a large range of demands. Scatter search was employed by Liberatore and Sechi in [33] to solve the optimal locations and operations of PRVs in a WDS.

2.2.4 Model of Pressure reducing valves

The PRV model usually comprises of three operation modes: *open*, *normal*, and *close* (or check valve mode) [53, 58]. However, in the formulation of optimization problem and the solution based on gradient methods for pressure regulations, the model of PRVs is commonly described by the Hazen-Williams equation and it is a two-mode model of PRV [37, 42]. In particular, this model can only represent the *normal mode* when a PRV maintains the downstream pressure at the preset value and the *open mode* when the downstream pressure is lower than the pressure setting. The NLP problem formulated with the two-mode model of PRVs may not have a solution due to the case that the check valve operation mode of PRVs occurs in WDSs, but it is not handled in the PRV model equation.

2.3 Summary about optimal pressure managements in WDSs

The optimization approaches to the optimal pressure managements in WDSs can be summarized as bellows:

- The optimal pressure management by regulating the pressure in WDSs reduces the leakage flow significantly [37, 42]. In addition, it is considered as one of the most effective means to decrease the magnitude of existing leakage flows and possibilities of creating new leaks.

- The optimal pressure management can be accomplished by optimization of locations and operations of PRVs. Although many solution approaches in which most of them are meta-heuristic approaches have been applied to solve these optimization problems [1, 31, 32, 33, 35, 48], these approaches own their limitations such as: 1) they require a large amount of computation time, 2) they result in low quality solutions, 3) they are only applicable to solve the optimization problems for small-scale WDSs [51], and 4) they employ PRV models which are not capable of representing full operation modes of PRVs [37, 42] in the formulations of optimal pressure management problems.

In this thesis, the optimal localization of PRVs will be considered. In particular, a new solution approach, namely mathematical program with complementarity constraints, will be proposed to solve the optimization problem efficiently. Also, an extended PRV model representing fully operation modes of PRVs will be introduced and applied to solve the optimal pressure management problems in WDSs.

2.4 Optimization of energy and maintenance costs for water supply and distribution systems

There are many optimization algorithms which have been developed in the literature to carry out the operational optimization of water supply and distribution systems. The optimization model plays a central role in the algorithms. There are several kinds of optimization models which can be classified into linear programming, mixed integer linear programming, mixed integer nonlinear programming, and simulation based model (e.g., model in EPANET), and Artificial Neural Network model (ANN). First, this section reviews the optimization models and then the algorithms which have been used so far to solve the optimization problems. Summaries will be presented in the last section.

2.4.1 Optimization model

2.4.1.1 The mass-balance model

The mass-balance model is considered as the simplest model. The system flow rate is determined by the demand plus the flow rate variation in a tank. Only the linear equation relating to the change of water levels with the system flow is used. The pressure requirement for obtaining the flow of water in the tank as well as the minimum pressures at nodes is neglected. This is based on the assumption that as the water levels in tank remains in a specified range of values, the pressures at nodes will be ensured to be larger than a minimum allowable value. The mass balance model is mainly employed for water supply systems instead of water distribution systems [61]. In the water supply system, pump stations supply water to the tanks through a main pipe line system. The total dynamic pump heads are calculated by the summation of the static head and the head loss in the pipe [19]. The resulting optimization is a mixed integer nonlinear programming problem with linear constraints and nonlinear objective function in which binary variables were introduced to represent on/off operations of pumps [3, 19]

2.4.1.2 The regression model

This model is more accurate than the mass-balance model as it captures the nonlinearity of hydraulic characteristics of the system. Several strategies can be used to model the non-linear equations that represent the hydraulic conditions of the WDS. For example, the specified pump combinations, demand scenarios, initial water tank levels are inputs for carrying out simulation. The output can be the energy cost, tank water flow rates, pressures at substantial nodes. The curves (quadratic or cubic polynomials) relating the output and input can be established by using interpolation of data points. The advantage of the regression model lies in the fact that the hydraulic quantities can be calculated in a very efficient computation manner and appropriate for online or fast optimal control [15, 62]. However, the regression model must be calculated again as there is any change in the system configuration and demand.

2.4.1.3 The simplified hydraulic model

This model is considered as an intermediate model between the regression model and the full hydraulic model [61]. In particular, the system hydraulics may be approximated using a macroscopic system model [61] or using a system of linear hydraulic equations. In the macroscopic system model, a highly skeletonized system model is used. Typically, only a pump, a lumped demand, and lumped resistance term of a pipe are included in an optimization model. In particular cases, some linear equations are enough to represent the system hydraulics [61, 63]. Jowitt and Germanopoulos in [64] developed a LP model relying on assumptions that decouplethe pumping station operation from the network hydraulic characteristics (e.g., the pump station flow reaching each reservoir can be expressed directly in terms of the pump control at station and is not affected by pump and valve controls elsewhere in the system).

2.4.1.4 Linearized model

A methodology for the derivation of this model is to linearize the hydraulic nonlinear equations around the given operating point [65] or using the iterative linearization scheme [66].The LP model is tractable in computation and hence it is widely employed for online optimal control [65]. However, using LP model, only continuous flow set points for pumps (or pump stations) are determined. Hence, a second optimization step is needed to translate the continuous set points (e.g., pump flows) to 0/1 operations of pumps [18, 65, 67, 68]. In particular, Giacomello et al. in [65] passed the solution of the LP model (i.e. a nonzero pump flow means that the pump operates, otherwise it is closed) to a stochastic search to improve the 0/1 operation of pumps.

2.4.1.5 The full hydraulic model

This model or nonlinear model is based on the energy and mass conservation laws. In contrast to the mass-balance and regression models, the full hydraulic model are adaptive to both system changes and spatial demand variations [61]. To account for the on/off operation of pumps, the optimal pump scheduling problem is formulated as a MINLP problem [18, 43, 69]. The full hydraulic model is also implemented in the EPANET software which allows incorporating if-then-rules for manipulating the discrete operations of pumps and valves.

According to optimization models, many solution approaches have been proposed such as dynamic programming (DP), meta-heuristic algorithms [20], hybrid GA [70], linear programming [65, 71] combined with a heuristic method, and NLP algorithm combined with a heuristic discretization algorithm[72].

2.4.2 Solution approaches to solve the optimal pump scheduling problems

2.4.2.1 Dynamic programming

Dynamic programming (DP) has been used to solve the optimal operation of pumps. The optimization problem was formulated in which water tank levels are state variables. The operation of pumps was found so as to minimize the energy cost while satisfying bound constraints of nodal pressure heads, water tank levels. The mass balance with the lumped demand or the regression model was widely used in conjunction with the DP method [15, 61]. To solve the optimization problem with the DP method, the optimization problem was broken into a series of discrete time steps or stages. Each stage has prescribed set of pump combinations and water tank levels. The optimal solution was obtained by evaluating all the state transitions between the adjacent stages instead of all state transitions between the stages (enumeration). The DP was efficient in obtaining the optimal solution for the small-scale system with a single tank. Zessler and Shamir in [73] used an iterative dynamic programming (DP) method that found an optimal pump scheduling for 24 hours given demands, the initial and final water levels in the tanks. Lansey and Awumah in [15] developed an online optimization of pump scheduling with consideration of pump switching using the DP method. The curves relating the energy consumption, rate of water level change with initial tank levels, needed for online optimization, were calculated offline while the optimization problem was solving on-line. To solve the optimization problem with DP, in each stage, each pump combination was evaluated with all initial tank levels. When all pump combinations for all states have been examined, the minimum cost for each pump combination for each ending state is retained. The algorithm moves to the next stage then continue until all stages have been examined. The optimal combinations of pumps are selected as providing the lowest energy cost in the planning time period.

Although DP is efficient in computing manner, it was mostly used for small-scale water supply systems or a single pressure zone with limited number of storage tanks [15, 61]. For a water supply network with many tanks, the state space for DP becomes too large and the computational burden would be very high [16, 61]. To overcome such complexity, the spatial decomposition approach was used in which a WDS with multiple storage tanks is broken into subsystems with one or two storage tanks. Optimal operations were carried out for each subsystem and were coordinated by a upper control level [15, 61].

2.4.2.2 Nonlinear programming and mixed integer nonlinear programming

Brion and Mays [74] as well as Ormsbee and Reddy [62] used NLP for operation optimization of pumping stations in a WDS, where a simulation model (i.e., KYPIPE) was used. The problem was solved using a generalized reduced gradient method (i.e., in GRG2 [75]) to determine operating time periods of pumps which were then passed to the simulation model to calculate the state and constraint values. The procedure is repeated until the convergence is reached. Zhong et al. in [76] also used a two-stage hierarchical scheme to optimize pump operations. In the first optimization stage, the NLP problem was formulated and solved by the augmented Lagrange and active set method to determine optimal head set-points for pump stations. In the second optimization stage, dynamic programming was used to translate the optimal head set-points into discrete operation of pump combinations. Yu et al. in [77] used the generalized reduced gradient method for determining the optimal operation of general water distribution systems with multiple sources and reservoirs. The optimization problem was formulated and solved with given 24 forecasted demands, initial and final water tank levels. The method starts with a feasible initial guess and iterates so that all the intermediate solutions are feasible. Sakarya and Mays in [78] presented a methodology to determine the optimal pump scheduling problem in water distribution system with water quality consideration. Also, a nonlinear optimization solver (GRG2) was coupled with a hydraulic simulator to address the optimization problem. For large-scale WDSs, nonlinear programming (NLP) and mixed-integer nonlinear programming (MINLP) has been applied to determine optimal pumping schedules of single and variable speed pump stations [8, 14, 18, 43]. This method consists of two optimization levels [8, 18, 68]. A relaxed NLP problem was solved in the first level optimization and a mixed-integer solution was found in the second level [8, 18]. The drawback of the approach lies in the fact that solving the MINLP in the second optimization level by available MINLP algorithms is difficult and it usually takes a large computation time. In addition, due to the challenges from treating discrete variables and handling non-convex equations, the solution of a large-scale MINLP suffers from a lack of robustness, reliability and efficiency [50]. To address the issue, a simple heuristic method was proposed by Skworcow et al in [72] to discretize the continuous solution to the discrete one. According to the method, fractional values of numbers of pumps in operation (i.e., 2.5 pumps) from NLP solution are translated into a series of discrete number of pumps switched on in discretized time intervals (i.e., 15 or 30 minutes). The discretized pumping schedules are passed to Epanet 2 for evaluating and improving the accuracy. The advantage of combining NLP algorithm with a heuristic discretization procedure lies in the fact it is simple to implement and the solution can be obtained in a short computation time [72]. Cembrano et al. in [69] proposed a penalization approach to penalize the non-integer variables (e.g., number of pumps switched on) in the optimization problem. The optimization was finally solved by using a generalized reduced gradient method.

Burgschweiger et al. in [8] developed an optimization model and a two-stage solution approach for operation of a large-scale WDS. In the first optimization stage, an aggregated model for pumps in each waterworks was developed. The NLP was then formulated and solved for the overall network with a continuous aggregated output for each pump station. In the second optimization stage this optimal continuous output is approximated by solving a small scale mixed integer nonlinear problem to determine on/off operations of pumps in each pump station in the WDS [8, 79].

Mouatasim in [19] formulated a MINLP problem for operational optimization of a water supply system with multiple reservoirs. Instead of using a MINLP solver, the author proposed to solve the optimization problem by a random perturbation of a reduced gradient method. Better results were shown than those obtained from solving the same problem by using a global MINLP solver. Although this solution approach is promising, it is only applied to solve small-scale pump scheduling problems up to 10 pumps with 10 binary variables [19]. In addition, the MINLP problem is only formulated for several time intervals without considering the dynamic changes of water levels in reservoirs and moreover, and pump switching was not considered in the study.

Recently, Ghaddar et al. in [80] presented a two-level optimization approach to solve the pump scheduling problem in water networks. In particular, a Lagrangian decomposition approach was used to decompose the large-scale MINLP problem into smaller scale MINLP problems. Then the best lower bounds of the optimization problem in each time interval are found by solving the corresponding Lagrangian master problems and the sub MINLP problems. Since the solutions from the Lagrangian decomposition algorithm may not feasible for the original MINLP problem, a limited discrepancy search in [81] was used to transform the infeasible solution to a feasible one.

2.4.2.3 Linear programming and Mixed integer linear programming

Jowitt and Germanopoulos in [64] presented a linear programming model to optimize the pump scheduling problem in a water supply system. The nonlinear network equations were linearized and their parameters are determined by using the extended-period simulation. McCormick and Powell in [16] proposed to use a mixed integer linear programming model (MILP) for operational optimization of a water distribution system. The binary variables represent hourly on/off operations of combinations of pumps in each pump group [16]. To solve the large scale MILP problem, a progressive solution approach was proposed. At first, the MILP is relaxed and solved by a linear solver. Then, the 0 and 1 values of relaxed binary variables are frozen, while fractional values of relaxed binary variables in only one or two time intervals are declared as binary variables in the MILP problem. A mixed integer solution is found and this procedure is repeated until binary decisions have been made for all time intervals [16]. Finally, a greedy algorithm was used to further improve the quality of the binary solution. This approach has been applied to the optimal pump scheduling problem for a system with 13 sources, 10 reservoirs, and 35 pumps [16].

2.4.2.4 Meta-heuristic approach

Genetic algorithms (GAs) and multi-objective evolutionary algorithms (MOEA) have been extensively used to optimize the design and operation of WDS [12, 20, 70, 82]. Due to no requirement of gradient computation, GAs can be applied to complex, nonlinear, combinatorial optimization problems [83, 84, 85]. However, a major disadvantage of GA lies in that, while it is efficient in finding the region of optimal solution, it is much less efficient in identifying the local optimum inside this region [70]. For this reason, a GA requires high computational intensity to reach the optimal or near an optimal solution [11, 65, 86, 87].

To improve the efficiency of GA, a hill-climber search algorithm (Hook and Jeeves algorithm) was coupled to GA in order to find a local optimum [70]. Also, to accelerate the computation of the GA, artificial neural networks (ANNs) were used as simulation models for carrying out optimization [86, 88] with which the computation time can be significantly reduced. However, an ANN model requires high computational burden in developing the model by training the ANNs [86]. The advantage of the use of meta-heuristic algorithm is due to the flexible formulation of the optimization problem. For examples, instead of defining explicitly the pump operation using binary variable in each hour, it is possible to define the time periods for pump operations (i.e., continuous variable) or tank levels as decision variables. With such reformulation, the number of decision variables in the optimization problem is significantly reduced [89]. Another advantage of the genetic algorithm is due the possibility of utilizing parallel computation to accelerate the GA solution procedure [89, 90]. The reason lies in the fact that carrying out simulation for each individual of a population in GA is independent, and hence they can be in parallel implemented. Parallel computation can be achieved by using the message passing interface programming or Open-Multi-Processor programming [90].

Bargio et al. in [38] proposed a novel approach for modeling the pump scheduling problem explicitly so as to minimize the operating cost. According to the approach, the pump start/end run times are considered as continuous decision variables. In addition, binary variables are introduced to describe the statuses of pumps at the beginning of the scheduling period. The optimization is formulated as a mixed integer nonlinear programming problem (MINLP). To solve the problem, the authors proposed to use the combination of grid search with the Hooke-Jeeves pattern search. At first, a set of feasible combinations of start/end run times and on/off states of the pumps at the beginning period is determined. Then, Hooke-Jeeves method was used to further improve each feasible combination (or solution). The final solution was chosen as the best one among the feasible solutions. The approach was efficient to solve the pump scheduling problems for small-scale WDS benchmarks. However, feasible combinations of on/off pumps and start/end time runs (Grid search) are not easily identified for large-scale WDSs with multiple pump stations.

2.4.2.5 Linear programming and hybrid approach

Pasha and Lansey. 2009 in [71] presented an approach for optimal pump scheduling to minimize energy cost in WDS. A linear programming (LP) problem was formulated based on the mass balance model and the regression method. In particular, the objective function relating the pumping energy cost with pump station flow and tank level was approximated by a linear function by using the regression method. The data for the approximation is produced by simulating a water distribution system with specified water tank levels and pump combinations. Solution of the linear programming problem provides the continuous flow set- points for pump stations. Scheduling algorithms such as integer programming and stochastic search can be used to translate the continuous flow set-points into 0/1 operation of pumps or pump combinations. Although this approach is very efficient in computation time since solving LP problem requires a very short computation time, the formulation of LP model for the systems with many tanks and many pump stations is not a trivial task. Puleo et al. in [67] translated the LP solution to the discrete one and used it as an initial solution for the hybrid discrete dynamically dimensioned search [91] to further improve the discrete pump scheduling.

A hybrid optimization scheme combining a linear programming (LP) method and a greedy algorithm was proposed by Giacomello et al. in [65] to solve the optimal pump scheduling problem. The LP model was derived by linearizing the nonlinear model equations around a given operating point. By solving the LP problem, for each time interval, pumps with zero flows will be switched off while (on/off) operation of pumps with nonzero flows will be further determined by the greedy algorithm coupled to EPANET 2. Similar to the approach in [71], this solution approach is suitable for application of real- time control. However, the operating point at which the LP model is derived must be given in prior. Price and Ostfeld in [92] proposed an iterative linearization approach to solve the optimal operation of a WDS. The non-linear and non-convex Hazen-Williams head loss was linearized and the resulting linear programming problem was solved iteratively until a defined convergence criterion is satisfied. The approach has been applied to minimize the annual operation cost of a water distribution system.

2.4.3 Summary about operational optimizations of water supply and distribution systems

The optimization models and solution approaches for operational optimizations of water supply/distribution systems can be summarized as bellows:

- Optimal operations of water supply and distribution systems, in general, are formulated as mixed integer nonlinear optimization problems (MINLPs) [8, 43]. The non-linear and non-convex MINLPs are usually very hard to solve. As an effort to relieve the complexity of the optimization problem, many optimization models are simplified to linear ones or use mass balance models which enable the optimization algorithms to solve the optimization problem easily. It is important to recognize that mass balance linear model is suitable for the water supply systems in which water is conveyed to reservoirs by main pipeline systems, whereas it is not the case for water distribution systems in general [61]. When a linearized or mass balance model is used to describe a water distribution system, the optimization model usually has low accuracy. Moreover, the continuous solutions for pump stations must be translated to on/off operations for individual pumps in pump stations [67, 71].

- GA [12, 20, 70] is considered as a general solution approach for solving the MINLPs for pump scheduling problems, but it requires an expensive computation time. In addition, although GA was mostly used for solving the operational optimizations of water distribution systems, it was usually applied for small-scale WDSs in the literature [14].

- A two stage optimization approach can be applied to solve large scale optimization problems. This is a promising approach, since it can solve large scale optimization problems in an reasonable computing time [8, 14, 18, 43].

In this thesis, we also consider the operational optimizations of water supply and distribution systems. For a water supply system, a general MINLP is formulated in which the constraints are mass-balance linear equations. We propose a set of linear inequality constraints to handle the number of pump switches (or the maintenance cost). These constraints as added to the MINLP problem will effectively restrict the number of pump switches and do not increase the complexity of the optimization problem significantly.

To optimize operation of a water distribution system in such an efficient manner, we implement the two-stage optimization approach for solving a real and large scale drinking water system in a software package. Different to many applications reported in the literature [14, 43], the computation framework proposed in this thesis is beneficial for large-scale WDSs.

Chapter 3

Modeling of water distribution systems and optimization methods

3.1 Modeling of water distribution systems

The aim of a water network is to supply water to customer or services. A small water distribution system may have a single source node such as an elevated service reservoir or a pumping arrangement directly supplying water from the treatment plant to the system, while a large network may have several sources nodes, service and balancing reservoirs and pumping stations. A water distribution system includes hydraulic components like *pipes*, *pumps*, *valves*, *reservoirs*, *storage tanks* which are classified into active and passive elements. Passive elements are pipes, reservoirs, storage tanks. They are parts of a water network and are used to transport the water to services and customers or to contain the water and supply water to the system by gravity. Pumps and valves are active elements. They are controlled by operators to lift water from lower areas to higher areas or/and to maintain pressures, flows (i.e., pressure reducing valves, flow control valves, etc.) in the system. Active and passive elements of a water distribution system are represented by hydraulic equations which are derived from continuity and energy principles for nodes (or junctions) and links, respectively. The energy principle or energy conservation is applied for incompressible flows on links. In a WDS, the Bernoulli's equation is used to establish equations describing pipes, valves, and pumps.

The model of a water distribution system with the control inputs and outputs is depicted in Fig. 3.1. The pump scheduling is a set of rules indicating pumps to be turned on or off (for single speed pumps) or indicating at which speed pumps operate (for variable speed pumps). Pressure control can be accomplished via regulating valve openings. The valve openings, and relative pump speeds are continuous control variables while the pump controls are binary or integer control variables [43]. A water distribution system is described by nonlinear differential algebraic equation [43]. The dynamic part is represented by storage tanks and the static nonlinear part by a hydraulic network [43]

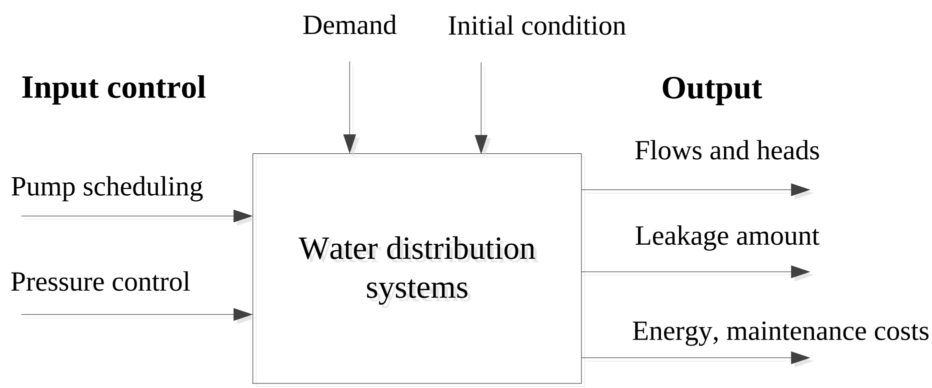


Figure 3.1: Modeling and optimizations of water distribution systems.

3.1.1 Pumps

Pumps or pump groups are installed in pipelines to supply extra head to lift water from a lower level to a higher level. In pipe systems, pumps may be placed externally and serve as supply pumps to provide water from external sources to the pipe systems, or may be placed internally within a system as booster pumps to boost up the pressure at some nodes within the system.

3.1.1.1 Single speed pumps

At a constant rotational speed, a pump has a relationship between the added head h_p and its discharge Q. This relationship is described by a quadratic function or a power law function [93]

$$h_p = a_p Q^2 + b_p Q + H_0 \tag{3.1}$$

$$h_p = H_0 - a_p Q^\alpha \tag{3.2}$$

where a_p,b_p, c_p are constants which are obtained by regression analysis from the data of pumps; H_0 is the shut-off head, i.e., the maximum head that can be provided by the pump as $Q \to 0$.

The power of a pump can be calculated by the following equation

$$P = \frac{\gamma Q h_p}{1000\eta} \tag{3.3}$$

where P is the power consumption in kilowatts; γ is the specific weight of the liquid in newton per cubic meter; Q is the pump discharge in cubic meters per second; h_p is the additional head added by the pump in meters and η is the pump efficiency.

The efficiency of pump can be approximated by a cubic polynomial function as [93]

$$\eta = A_\eta Q^3 + B_\eta Q^2 + C_\eta Q + D_\eta \tag{3.4}$$

It is due to the fact that Eq. (3.3) is complicated when used in the formulation of optimization problems [93], the power consumption of pump can be approximated by a cubic polynomial function of flow [93]

$$P = A_p Q^3 + B_p Q^2 + C_p Q + D_p \tag{3.5}$$

where A_p,B_p, C_p, and D_p are constants obtained by regression method from available pump data .

3.1.1.2 Variable speed pumps

For variable speed pumps, the scaling to relative pump speed is applied for discharge, head, and power of pumps using affinity laws [93]. The equations in Eq. (3.1) and (3.2) are scaled as bellows

$$h_p = s^2 \left(a_p \left(\frac{Q}{s} \right)^2 + b_p \left(\frac{Q}{s} \right) + H_0 \right) \tag{3.6}$$

and

$$h_p = s^2 \left(H_0 - a_p \left(\frac{Q}{s} \right)^\alpha \right) \tag{3.7}$$

The efficiency equation in (3.4) is scaled to the speed of pump

$$\eta = A_\eta \left(\frac{Q}{s} \right)^3 + B_\eta \left(\frac{Q}{s} \right)^2 + C_\eta \left(\frac{Q}{s} \right) + D_\eta \tag{3.8}$$

Similarly, the power consumed by pumps can be scaled from Eq. (3.5) as bellows

$$P = s^3 \left(A_p \left(\frac{Q}{s} \right)^3 + B_p \left(\frac{Q}{s} \right)^2 + C_p \left(\frac{Q}{s} \right) + D_p \right) \tag{3.9}$$

3.1.1.3 A group of identical pumps

For a pump group with n identical pumps configured in parallel, the relationships between flow and head (h_p-Q), flow and efficiency (η_p-Q), flow and power consumption (P-Q) for a pump group are scaled to the number of pumps in operation and their speed [93]. In fact, we have

$$h_p = s^2 \left(a_p \left(\frac{Q}{ns} \right)^2 + b_p \left(\frac{Q}{ns} \right) + c_p \right) \tag{3.10}$$

or

$$h_p = s^2 \left(H_0 - a_p \left(\frac{Q}{ns} \right)^{\alpha} \right) \tag{3.11}$$

The efficiency can be scaled due to speed and number of operating pumps

$$\eta = A_\eta \left(\frac{Q}{ns} \right)^3 + B_\eta \left(\frac{Q}{ns} \right)^2 + C_\eta \left(\frac{Q}{ns} \right) + D_\eta \tag{3.12}$$

Similarly, the power consumption for a pump group is

$$P\left(Q,n,s\right) = \begin{cases} ns^3 \left[A_p \left(\frac{Q}{ns} \right)^3 + B_p \left(\frac{Q}{ns} \right)^2 + C_p \left(\frac{Q}{ns} \right) + D_p \right] & \text{if } n \neq 0 \\ 0 \qquad \text{if } n = 0 \end{cases} \tag{3.13}$$

3.1.2 Pipes

Pipes are used for transporting water to services. When a fluid flows through a pipe, a part of the total energy of the fluid is spent in maintaining the flow [94]. It is characterized by the head loss in the pipe. The head loss is classified into two categories: the head loss due to pipe friction is considered as major head loss, while the head loss caused by minor appearances (i.e., sudden change of flow or local obstruction to flow) is termed as minor head loss. Pipe friction loss is produced by the shear stress between the wall of the pipe and the fluid moving through the pipe. The shear stress developing within the fluid (i.e., water) depends on the fluid viscosity. The fluid with higher viscosity will result in higher shear stress and, consequently, a greater head loss across a pipeline [8, 95]. There are two formulas, mostly used for predicting the friction loss through a pipe, are Darcy-Weisbach and Hazen-Williams. The Darcy-Weisbach formula is dimensionally homogeneous, while the Hazen-Williams formula is empirical. The Darcy-Weisbach is regarded as the most accurate means of relating head loss and flow for the complete range of the Reynolds number, while the Hazen-Williams is less accurate and is applicable for a limited Reynolds number range [96, 97].

3.1.2.1 The Darcy-Weisbach equation

$$\Delta h = f \frac{8L}{\pi^2 g D^5} Q|Q| \tag{3.14}$$

The friction factor f depends on the Reynolds number (Re) and relative roughness of the pipe (ε/D). The friction is represented by a graph on the Moody diagram.

For laminar flow (Re ≤ 2000), f is calculated by the Hagen-Poiseuille equation

$$f = \frac{64}{\mathrm{Re}} \tag{3.15}$$

Turbulent flow with Re≥4000 includes smooth turbulent flow (or smooth pipe), transitional turbulent flow (between smooth and rough turbulent regions) and rough turbulent flow (or rough pipe).

The smooth turbulent flow occurs in a pipeline as the pipe wall roughness is within the laminar sub layer [94]. The friction factor depends only on the Reynolds number, and is calculated according to the Prandtl-von Karman equation

$$\frac{1}{\sqrt{f}} = 2\log\left(\frac{\mathrm{Re}\sqrt{f}}{2.51}\right) \tag{3.16}$$

The rough turbulent flow (rough pipe) is verified that , the effect of viscosity is negligible, and the friction factor depends only on the relative roughness (ε/D) and is computed by the Von-Karman equation as

$$\frac{1}{\sqrt{f}} = 2\log\left(\frac{3.7}{\varepsilon/D}\right) \tag{3.17}$$

For transition turbulent flows, the friction factors are estimated by the Colebrook-White equation. It depends on both ε/D and Re.

$$\frac{1}{\sqrt{f}} = -2\log\left(\frac{\varepsilon}{3.7D} + \frac{2.51}{\mathrm{Re}\sqrt{f}}\right) \tag{3.18}$$

where ε/D is the relative pipe roughness; and Re is the Reynolds number. The fiction factor f in the Darcy-Weisbach equation calculated by the Colebrook and White equation has been preferred because of its presumed superior accuracy and sound theoretical basis [98]. The Colebrook and White equation is valid for the Re ranging from 4×10^3 to 10^8 and values of relative roughness ε/D ranging from 0 to 5×10^{-2} [98]. The Colebrook and White equation is asymptotic to the equation for the smooth turbulent flow when $\varepsilon/D \to 0$ and the equation for rough turbulent flow when $\mathrm{Re} \to \infty$

Some notes on the Colebrook-White equations

The solution of the Colebrook and White equation in (3.18) is implicit and solved by an iterative numerical scheme such as the Newton-Raphson method or by the reference to Moody-diagram [98]. However, the iterative calculus can cause overburden in simulation of flows in a pipe system in which it is necessary to evaluate friction factor hundreds or thousands of times [99]. The reference to Moody-diagram to obtain friction factors is not convenient [98]. An alternative solution to the iterative methods is the direct use of an explicit equation which is precise enough to compute the friction factor. Recently, numerous researchers provide many explicit equations in [99, 100, 101], which are highly accurate in simulations of WDSs. A well-known explicit equation for calculating the friction factor given in (3.19) is proposed by Swamee and Jain (1976). This equation was also used in EPANET [58].

$$f = \frac{0.25}{\left[\log\left(\frac{\varepsilon}{3.7D} + \frac{5.74}{\mathrm{Re}^{0.9}}\right)\right]^2} \tag{3.19}$$

$$\mathrm{Re} = \frac{4\,|Q|}{\pi v D} \tag{3.20}$$

Although the friction factor can be explicitly calculated by Eq. (3.19), this equation is non-smooth (e.g., it is dependent on the absolute value of Q). Thus, the resulting optimization problem, e.g., operational optimization of water distribution systems, is non-smooth and cannot be solved by gradient based methods. The non-smooth Darcy-Weisbach head loss equation is approximated by a smooth one in section 3.2.2

3.1.2.2 The Hazen-Williams equation

The Hazen-Williams equation in Eq. (3.21) (G.S. Williams and A. Hazen 1933) is empirical and it is widely used in the design and modeling of water distribution network.

$$\Delta h = \frac{10.68L}{C^{1.852}D^{4.87}} Q|Q|^{0.852} \tag{3.21}$$

where C is the Hazen-Williams coefficient; L and D are length and diameter of the pipe in m, respectively; Q is the flow rate through the pipe in (m^3/s). The Hazen-Williams equation is more suitable for smooth pipes, i.e., new pipes with medium to large diameter [94]. To use the formula for old pipes (for most WDSs), the Hazen-Williams coefficient should be reduced or modified so as to obtain high accuracy of head loss [94]

3.1.3 Valves

Valves in WDSs are used to control the rate of flow (i.e., flow control valves), shut off pipelines (i.e., isolated valves), or reduce pressure (pressure reducing valve) for low elevation water supply areas, and prevent reserve flow (check valve) [94]. Considering a valve on a link which connects node i to node j. The head loss across the valve is calculated by [94]

$$H_i - H_j = K\frac{V^2}{2g} = \left(\frac{8K}{\pi^2 g D^4}\right) Q^2 \tag{3.22}$$

where K is the minor loss coefficient and is determined by the flow or by the shape of the valve and the aperture percent; V is the average velocity through the valve.

3.1.3.1 Check valves

Check valves are a special kind of flow control valves and allow the flow in one direction only. The state of closing or opening is managed by the valve itself. In particular, it opens when the flow is in the desired direction whereas it closes when the flow is in the opposite direction. Check valves are mainly used in suction and delivery sides of pumps

[94]. The following equation is used to describe the operation of a check valve on a link in direction $i \to j$ [102]

$$\max(0, H_i - H_j) = \frac{8K}{\pi^2 g D^4} Q^2 \tag{3.23}$$

It can be seen that as $H_i > H_j$, $Q > 0$, and whereas if $H_i < H_j$, $Q = 0$

3.1.3.2 Pressure reducing valves

A pressure reducing valve (PRV) is used to keep a constant pressure at the downstream node regardless of how large upstream pressure is [94]. For this reason, it is mostly used in WDSs in order to reduce system pressures and hence control leakage losses [103]. A PRV is characterized by the downstream pressure that it attempts to maintain, its controlling status and its valve resistance coefficient [104]. A PRV can operate in one of the three operation modes: *open* when the downstream pressure is less than the pressure setting of PRV, *normal* when the downstream pressure is limited by the pressure setting of PRV, and *closed* when the back flow is detected and the PRV acts as a check valve to prevent flow in opposite direction [94, 104].

$$H_j = \begin{cases} H_i - RQ^2, Q > 0 \text{ and } H_j < H_{set} & : open \\ H_{set} \quad , Q > 0 \text{ and } H_j > H_{set} & : normal \\ H_j \quad , Q = 0 \text{ and } H_i < H_j & : close \end{cases} \tag{3.24}$$

As a PRV operates in the *normal* mode, its resistance is a control variable and varies due to the head loss reduction [94]. We have

$$R = \left(\frac{H_i - H_{set}}{Q}\right)^{\frac{1}{2}} > \frac{8K}{\pi^2 g D^4} \tag{3.25}$$

where K is the head loss coefficient of PRV; H_{set} is the pressure setting.

3.1.4 Mass balance at nodes (or junctions)

The continuity equation for steady incompressible flow at a junction is defined that the sum of the mass flow rate entering a junction must be equal to the sum of the mass flow rate leaving it. Consider a node j

$$\sum_j Q_{i,j} - d_j - l_i = 0 \tag{3.26}$$

where d_i and l_i are demand and leakage amount at node i, respectively. Leakage l_i is calculated in section 3.1.7

3.1.5 Reservoirs

Reservoir is a considered as unlimited water supply source (i.e., lake). Mathematically, it is represented by a junction with a constant head $\overline{H}_i$.

$$H_i = \overline{H}_i \tag{3.27}$$

3.1.6 Storage Tanks

Tanks are often installed near consumption centers to supply water at sufficient pressure. They are also used to reduce the fluctuation of system pressure when demand changes or there are abruptions caused by switching on/off pumps. In addition, tanks can store water for the purpose of fire protection. Appropriate operation of filling- emptying of tank can help water utilities to reduce the pumping energy cost. In a WDS with a pumping system and tanks, as the rate of pumping exceeds the rate of demand, the tanks are filled and emptied with reserve condition. The model of a tank is described by the mass balance equation. Consider a storage tank i, the following equation is used

$$\frac{dV_{\mathrm{t},i}}{dt} = \sum_i Q_{ji} \tag{3.28}$$

where $V_{t,i}$ is the volume of water in the storage tank; Q_{ji} is flow coming in and out of the tank . If the tank has a constant cross-sectional area (e.g., a cylindrical tank), the water volume in the tank is

$$V_{t,i} = S_i h_{t,i} \tag{3.29}$$

where $h_{t,i}$ and S_i are the water level in the tank i and the cross-sectional area of tank i, respectively. Replacing this equation into Eq. (3.28), we have

$$S_i \frac{dh_{\mathrm{t},i}}{dt} = \sum_j Q_{ji} \tag{3.30}$$

Using the Euler integration method to discretize the differential equation in Eq. (3.30), we obtain the equation describing the relationship between the heads of tanks at two successive time intervals. The length of time interval is Δt.

$$h_{i,k+1} - h_{i,k} = \frac{\Delta t \sum_j Q_{ji}}{S_i} \tag{3.31}$$

where $h_{i,k}$ and $h_{i,k+1}$ are water levels in the tank i at time interval k and $k+1$, respectively.

3.1.7 Modeling of leakage

3.1.7.1 Leakage model in a water distribution system

The leakage includes background and burst leak components. The background leakage is due to small seepages through numerous connections, joints and fittings. The back ground leak is distributed over nodes and its magnitude is proportional to the pressure as shown in Eq. (3.32) [42]. In the continuity equation, it is considered as an additional demand.

$$l_i = c_i p_i^{\gamma} \tag{3.32}$$

where l_i is the leakage flow at node i; c_i is the leakage coefficient; γ is the leakage exponent and p_i is the pressure at node i. The leakage exponent depends on many factors described in the literature [7, 42, 47, 56]

Another equation for modeling of the background leakage (for a pipe) is to use the average pressures of two end nodes of pipes, namely p_i and p_j. The difference between this model and the model in Eq. (3.32) is due to the fact that the length of pipe (ij) is taken into consideration. The back ground leakage for a pipe is calculated as [7, 37, 47]

$$l_{ij} = c_{ij} L_{ij} \left[\frac{1}{2} \left\{ p_i + p_j \right\} \right]^{1.18} \tag{3.33}$$

where L_{ij} is the length of the pipe between node i and node j; c_{ij} is a constant value. This value is estimated based on the level of leakage and the corresponding average zonal pressures in the network [37] or based on the minimum night flows [47]. For modeling purpose, the distributed leakage flow at node i is calculated by the following equation

$$l_i = \frac{1}{2} \sum_{j \in J_i} l_{ij} \tag{3.34}$$

where J_i is a set of pipe connected to node i.

Araujo et al in [105] proposed a leakage flow model at node as following

$$\begin{aligned} l_i &= K_{f,i} p_i^{1.18} \\ K_{f,i} &= \frac{1}{2} c \sum_{j \in J_i} L_{ji} \end{aligned} \tag{3.35}$$

where c is the leakage coefficient.

3.1.7.2 Estimation of the parameters of the leakage model

There are several methods to estimate the parameters for the leakage model. The parameter c in Eq. (3.35) and c_{ij} in Eq. (3.33) are estimated due to the minimum night flows (MNF) and water balance. The estimation is usually carried out for a domestic meter area and a calibration model is used. The heuristic or trial and error algorithms are commonly used to solve the calibration problem.

One method is proposed by Araujo et al in [105]

Araujo et al in [105] proposed a method to estimate the leakage flow at distributed nodes in the network. At first, the leakage coefficient c in Eq. (3.35) is estimated using the minimum night flow (Q_{MNF}), and then the nodal demand is reallocated for each time step. In particular, parameter c is estimated by solving the following optimization problem [105] where the leakage model in Eq. (3.35) is used.

$$\begin{aligned} \min \ f(\Delta Q) &= \frac{(0.8Q_{MNF} - Q_{F,t_{\min},Mod})}{0.8Q_{MNF}} \\ Q_{F,t_{\min},Mod} &= 0.5 \times c \times \sum_{i=1}^{N} \left(p_i^{1.18} \times \sum_{j=1}^{M} L_{ji} \right) \end{aligned} \tag{3.36}$$

Wwere index $_{Mod}$ denotes the value calculated by the model in EPANET

The demand pattern $f_{c,t}$ for 24 hours should be calibrated since the model now takes the leakage dependent pressure into account. Now the total flow in the model is calculated by

$$Q_{T,t} = \sum_{i=1}^{N} (q_{bi,t} \times f_{c,t}) + \sum_{i=1}^{N} \left(K_{f,i} p_{i,t}^{1.81} \right) \tag{3.37}$$

where $q_{bi,t}$ is base demand at node i.
The parameter $f_{c,t}$ for 24 hours are estimated by solving the least square optimization problem. The objective function is the square of the deviation between the measured system flow ($Q_{m,t}$) and modelled system flow ($Q_{T,t,mod}$)

$$\min \ f(\Delta Q_{T,t}) = \sum_{t=1, t \neq t_{\min}}^{24} \frac{(Q_{m,t} - Q_{T,t,Mod})^2}{Q_{m,t}} \tag{3.38}$$

Genetic algorithms coupled to EPANET [106] were used to address the two above optimization problems.

The second method is proposed by Ulanicki et al in [42]

The second approach is described in [42] and following equations are used to estimate parameter c_i in Eq. (3.32).

$$Q_{MNF} = \sum_{i=1}^{N} c_i p_i^{1.1} = \sum_{i=1}^{N} \beta d_i p_i^{1.1} \tag{3.39}$$

where d_i and p_i denote the demand flow and pressure of node i at the time of minimum flow, respectively. The unknown leakage coefficient c_i is proportional to the demand flow of node d_i [42] by a common constant factor β. And this factor is calculated by the following equation

$$\beta = \frac{Q_{MNF}}{\sum\limits_{i=1}^{N} d_i p_i^{1.1}} \tag{3.40}$$

3.2 Smoothing non-smooth equations in the water system

3.2.1 Smoothing non-smooth equations

In this thesis, we use the gradient based optimization methods to solve the optimization problem. It requires that the model is smooth and continuous. The following non-smooth terms are used in the thesis and they are approximated by the smooth ones [102].

$$|Q| \approx \sqrt{Q^2 + \epsilon^2} \tag{3.41}$$

and

$$\max\left(Q_1, Q_2\right) \approx \frac{1}{2}\left(Q_1 + Q_2 + \sqrt{\left(Q_1 - Q_2\right)^2 + \epsilon^2}\right) \tag{3.42}$$

where ϵ is a small number.

3.2.2 A smooth model of Darcy-Weisbach equation

Although the Darcy-Weisbach equation is theoretically sound and very accurate for describing the pipe head losses, it has not been widely used in gradient-based WDS optimization. This is due to its non-smooth expression which leads to difficulties in the gradient computation. The non-smooth Darcy-Weisbach equation was approximated by a smooth one in [8]. The approximation is made on the turbulent flow range. This approximation is appropriate, since turbulent flows are dominant in operations of water distribution systems [95]. The non-smooth Darcy-Weisbach equation is expressed as

$$\Delta H = sign\left(q\right) f \frac{L}{D}\frac{V^2}{2g} \tag{3.43}$$

which is correlated, for friction factor f, with the Colebrook-White equation

$$\frac{1}{\sqrt{f}} = -2\log\left(\frac{(\varepsilon/D)}{3.7} + \frac{2.51}{\mathrm{Re}\sqrt{f}}\right) \tag{3.44}$$

where Re is the Reynolds number and is described by

$$\mathrm{Re} = \frac{VD}{\nu} \quad and \quad V = \frac{4\left|Q\right|}{\pi D^2} \tag{3.45}$$

In Eq. (3.44) and Eq. (3.45), V is the average velocity of water, ν is the viscosity of water, ε is the roughness coefficient of pipe. L, D, and g are the pipe length, the pipe diameter, and the acceleration of gravity, respectively. The head loss in Eq. (3.43) depends on Q. For a given value of q, the nonlinear equations ((3.43),(3.44) and (3.45)) can be solved to obtain Δh. Since the flow rate Q can be in both directions, the absolute value has to be used for Q in Eq. (3.45) and $sign(Q)$ in Eq. (3.43). This leads to a non-smooth relation which causes a serious difficulty in gradient computations for solving the optimization problem by a gradient-based method.

A smoothed model

We consider the flow in the forward direction $Q \geq 0$, therefore $sign(Q) = 1$ and $|Q| = Q$. The Eq. (3.44) can be written in the following form

$$\frac{1}{\sqrt{f}} = -2\log\left(\frac{\varepsilon}{3.7D}\right) - 2\log\left(1 + \frac{3.7 \times 2.51}{\mathrm{Re} \times \sqrt{f} \times \varepsilon \big/ D}\right) \tag{3.46}$$

For the sake of simplicity, we define

$$z = \frac{3.7 \times 2.51}{\mathrm{Re}\sqrt{f}\varepsilon \big/ D} \tag{3.47}$$

Denote Re^* as the boundary value of Re of the range between the transitional and rough turbulent flow and there is [97]

$$\frac{1}{\sqrt{f}} = \frac{\varepsilon}{D}\frac{\mathrm{Re}^*}{200} \tag{3.48}$$

From Eq. (3.47) and (3.48) there will be $z \ll 1$ for any $\mathrm{Re} \geq \mathrm{Re}^*$. Therefore,

$$\ln(1+z) = z - \frac{z^2}{2!} + \frac{z^3}{3!} - .... \simeq z \tag{3.49}$$

Now the Eq. (3.46) can be written as [107]

$$\frac{1}{\sqrt{f}} = -2\log\left(\frac{\varepsilon}{3.7D}\right) - 2\frac{\ln(1+z)}{\ln(10)} \simeq -2\log\left(\frac{\varepsilon}{3.7D}\right) - \frac{2}{\ln(10)}z \tag{3.50}$$

Let $\frac{1}{\sqrt{f_k}} = -2\log\left(\frac{\varepsilon}{3.7D}\right)$, which is known as the Karman-Prandtl equation [94]. The friction factor f_k is independent of Re and only a function of ε/D. Thus the Eq. (3.50) becomes

$$\frac{1}{\sqrt{f}} = \frac{1}{\sqrt{f_k}} - \frac{2}{\ln(10)}z \tag{3.51}$$

For $Q \geq 0$, replace z with Eq. (3.47), $\mathrm{Re} = \frac{VD}{\nu}$, and $V = \frac{4Q}{\pi D^2}$ into the Eq. (3.51), we can obtain the following friction factor function [8]

$$f = f_k\left(1 + \frac{\delta}{Q}\right)^2 \tag{3.52}$$

where

$$\frac{1}{\sqrt{f_k}} = -2\log\left(\frac{\varepsilon}{3.7D}\right) \tag{3.53}$$

$$\delta = \frac{2\alpha}{\beta \ln(10)} \tag{3.54}$$

with

$$\beta = \frac{\varepsilon}{3.7D} \tag{3.55}$$

$$\alpha = \frac{2.51}{4/\pi v D} \tag{3.56}$$

Eq.(3.53) is known as the Karman-Prandtl equation. Using Eq. (3.52) for an approximation of f, the head loss in Eq.(3.43) becomes

$$\Delta H = R_p \left(Q^2 + 2\delta Q + \delta^2\right) \tag{3.57}$$

where $R_p = \frac{8Lf_k}{\pi^2 g D^5}$. This equation is asymptotically corrected to a constant $R_p \ln(\beta)$ [8]. Therefore the asymptotic approximation of head loss (ΔH^a) is

$$\Delta H^a = R_p \left(Q^2 + 2\delta Q + (\ln(\beta) + 1)\,\delta^2\right) \tag{3.58}$$

To describe the flow rate in both directions, an approximation $Q \simeq \sqrt{Q^2 + a^2}$ is used, and hence the following smooth equation (ΔH^s) is proposed

$$\Delta H^s = R_p Q \left(\sqrt{Q^2 + a^2} + b + \frac{c}{\sqrt{Q^2 + d^2}}\right) \tag{3.59}$$

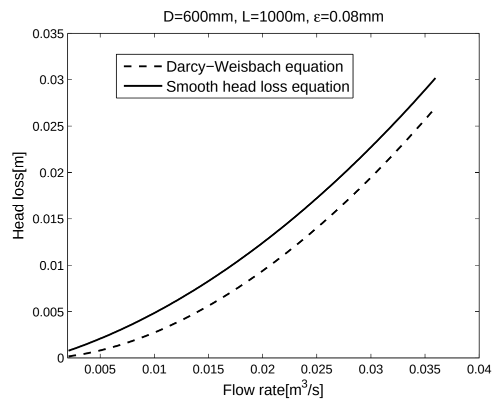
The parameters a,b,c, and d for the smooth head loss are estimated by using asymptotic correctness between the smooth head loss equation in (3.58) and (3.59)[8]. To the end, with a given slope of the smooth head loss (i.e., K_s) at a zero flow (Q=0), following equations relating the parameters are deduced [8]:

$$\begin{aligned} &b = 2\delta \\ &c = (\ln(\beta) + 1)\,\delta^2 - \frac{a^2}{2} \\ &R_p\left(a + b + \frac{c}{d}\right) = K_s \end{aligned} \tag{3.60}$$

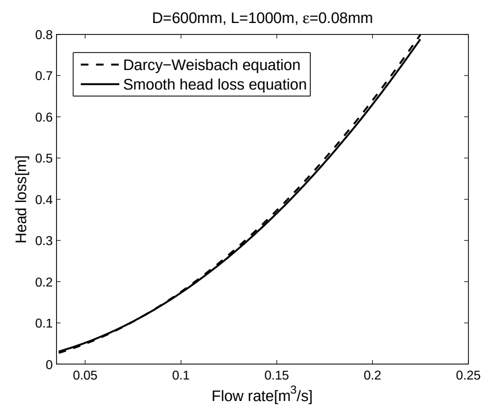
To evaluate the accuracy of the smooth head loss, we calculate the parameters c and d for the smooth head loss of a pipe with different diameters. Parameters K_s and a are chosen as 0.35 and 1.e-6, respectively. The results are given in Table 3.1. The comparisons of the smooth head loss with the non-smooth Darcy-Weisbach equation are shown in Fig. 3.2 for the different ranges of flows and different roughness coefficients. It can be seen in this figure that the accuracy of the smooth head loss varies according to the range of flows and the relative roughness factors ε/D . In particular, the smooth head loss will attain higher accuracy for pipes with larger relative roughness factors and it is true reversely. This is because the rough turbulent range of the flow for a pipe with a large relative roughness factor extends to the left side of the moody diagram and the approximation of the smooth head loss in Eq. (3.59) with parameters a,c, and d is made on a narrow range of flows, hence it achieves the high accuracy. For smooth pipes with small relative roughness factors, the head loss equation in Eq. (3.59) with the parameters a,c, and d cannot compensate the errors caused by Eq. (3.49) in a wide range of flows, thus it attains low accuracy.

Table 3.1: Parameters for the smooth head loss with ε=0.08(mm), K_s=0.35, and a=1.e-6

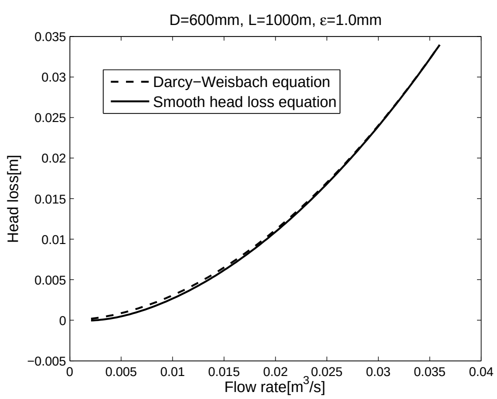
D(mm)	c	d
80	-2.000e-6	0.002
100	-6.000e-6	0.0032
150	-3.000e-5	0.0077
200	-9.800e-5	0.014
300	-5.210e-4	0.035
375	-1.305e-3	0.059
400	-1.701e-3	0.069
600	-9.009e-3	0.247



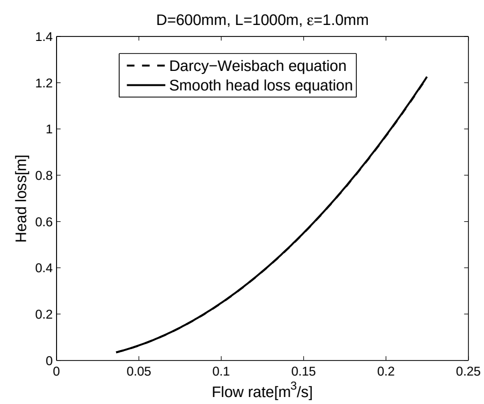
(a) Small flow rates



(b) Large flow rates



(c) Small flow rates



(d) Large flow rates

Figure 3.2: Darcy-Weisbach and its smooth equation with ϵ=0.08(mm), K_s=0.35, a=1.e-6

3.3 Simulation of water distribution systems

3.3.1 The Newton- Raphson method

The model equations for a general network includes equations describing components available in a WDS such as pipes, nodes, reservoirs, storage tanks, pumps stations and valves. Among these equations, equations for nodes are linear equations, while the others are nonlinear ones. The set of equations for a WDS can be represented in which nodal heads are unknown only or both flows and nodal heads are unknown [94].

Here, a set of nonlinear equations relating unknown nodal heads and link flows for a water distribution system is solved by using the Newton-Raphson method. Given initial values of link flows ($\mathbf{Q^0}$), nodal heads and link flows are computed by solving a system of linearized equations iteratively [4, 56] until a defined convergence criterion is satisfied.

Consider the WDS with NP links, NR reservoirs and tanks, NJ nodes. The nonlinear model equations of a WDS can be written in a general form as following [4]

$$f\left(\mathbf{Q},\mathbf{H}\right) = \begin{pmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{12}^T & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{Q} \\ \mathbf{H} \end{pmatrix} - \begin{pmatrix} \mathbf{A}_{10}\mathbf{H}_0 \\ \mathbf{d} \end{pmatrix} = \mathbf{0} \tag{3.61}$$

where $\mathbf{H}_0$ is the column vector of the head of the source nodes and reservoirs; $\mathbf{Q}$ is the column vector of the link flows with NP elements; $\mathbf{d}$ is the given nodal demand, column vector of NJ- NR elements; $\mathbf{A}_{12}$ is the connectivity matrix of edges- to nodes (without reservoir/ tank nodes) NP x (NJ-NR); $\mathbf{A}_{12}^T$ is the transpose of matrix $\mathbf{A}_{12}$; $\mathbf{A}_{10}$ is the connectivity matrix edge-reservoir/tank node (NP x NR); $\mathbf{A}_{11}$ is a diagonal matrix with NP x NP elements. The value of the diagonal element is $\frac{\Delta h_i^k}{Q_i^k}$ (i.e., $R_i\left|Q_i^k\right|^{n-1}$ for pipe and $\frac{a}{Q_k^i} + b|Q_k^i|^{\alpha-1}$ for pumps);k is the gradient iteration counter.

At iteration k, the set of linear equations approximated from Eq. (3.61) by using Taylor expansion is

$$\begin{pmatrix} \mathbf{G} & \mathbf{A}_{12} \\ \mathbf{A}_{12}^T & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{Q}^{k+1} \\ \mathbf{H}^{k+1} \end{pmatrix} = - \begin{pmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{12}^T & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{Q}^{k} \\ \mathbf{H}^{k} \end{pmatrix} + \begin{pmatrix} \mathbf{A}_{10}\mathbf{H}_0 \\ \mathbf{d} \end{pmatrix} + \begin{pmatrix} \mathbf{G} & \mathbf{A}_{12} \\ \mathbf{A}_{12}^T & \mathbf{0} \end{pmatrix} \begin{pmatrix} \mathbf{Q}^{k} \\ \mathbf{H}^{k} \end{pmatrix} \tag{3.62}$$

where $\mathbf{G}$ is a diagonal matrix of NP x NP elements. The diagonal elements are derivatives of pipe head loss or pump additional head with respect to flow (i.e., $nR_i\left|Q_i^k\right|^{n-1}$ for pipe and $\alpha b|Q_k^i|^{\alpha-1}$ for pumps).

After several mathematical derivations, we obtain the following linear system for updated nodal heads and link flows

$$\mathbf{G}\mathbf{Q}^{(k+1)} + \mathbf{A}_{12}\mathbf{H}^{(k+1)} = -\mathbf{A}_{11}\mathbf{Q}^{(k)} + \mathbf{A}_{10}\mathbf{H}_0 + \mathbf{G}\mathbf{Q}^{(k)} \tag{3.63}$$

And

$$\mathbf{A}_{12}^T\mathbf{Q}^{(k+1)} = \mathbf{d} \tag{3.64}$$

Multiplying the equation Eq.(3.63) with $\mathbf{A}_{12}^T\mathbf{G}^{-1}$, we have

$$\mathbf{A}_{12}^T\mathbf{Q}^{(k+1)} + \mathbf{A}_{12}^T\mathbf{G}^{-1}\mathbf{A}_{12}\mathbf{H}^{(k+1)} = \mathbf{A}_{12}^T\mathbf{G}^{-1}\left(\mathbf{G} - \mathbf{A}_{11}\right)\mathbf{Q}^{(k)} + \mathbf{A}_{12}^T\mathbf{G}^{-1}\mathbf{A}_{10}\mathbf{H}_0 \quad (3.65)$$

Replace equation Eq.(3.64) to equation Eq.(3.65), we obtain the following equation for calculating updated nodal heads

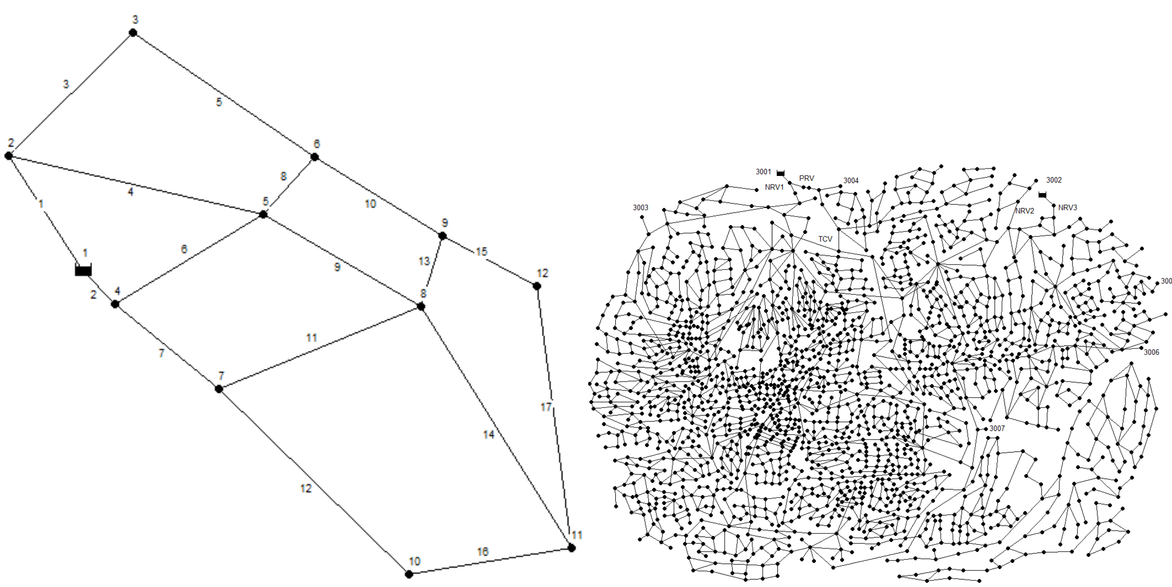
$$\left(\mathbf{A}_{12}^T\mathbf{G}^{-1}\mathbf{A}_{12}\right)\mathbf{H}^{(k+1)} = -\mathbf{A}_{12}^T\mathbf{G}^{-1}\left(\mathbf{A}_{11}\mathbf{Q}^{(k)} + \mathbf{A}_{10}\mathbf{H}_0\right) + \left(\mathbf{A}_{12}^T\mathbf{Q}^{(k)} - \mathbf{d}\right) \quad (3.66)$$

and the equation for calculating updated link flows

$$\mathbf{Q}^{(k+1)} = \left(\mathbf{I} - \mathbf{G}^{-1}\mathbf{A}_{11}\right)\mathbf{Q}^{(k)} - \mathbf{G}^{-1}\left(\mathbf{A}_{12}\mathbf{H}^{(k+1)} + \mathbf{A}_{10}\mathbf{H}_0\right) \quad (3.67)$$

It can be seen that equation Eq.(3.66) is a linear system which can be written as $\mathbf{Ax} = \mathbf{b}$. where matrix $\mathbf{A} = \mathbf{A}_{12}^T\mathbf{G}^{-1}\mathbf{A}_{12}$ is sparse, symmetric, and positive definite [108]. After solving the linear system to get $\mathbf{H}^{(k+1)}$, we replace this vector to equation Eq.(3.67) to obtain $\mathbf{Q}^{(k+1)}$. The iterative procedure will be terminated (e.g., solution is convergent) until the convergent criterion in Eq. (3.68) is satisfied:

$$\frac{\sum_{i=1}^{n_Q}\left|Q_i^{k+1} - Q_i^k\right|}{\sum_{i=1}^{n_Q}\left|Q_i^{k+1}\right|} \leqslant \delta_{stop} \quad (3.68)$$



(a) (b)

Figure 3.3: A test network in [4] and EXNET water distribution system in [5]

Table 3.2: Data of the network

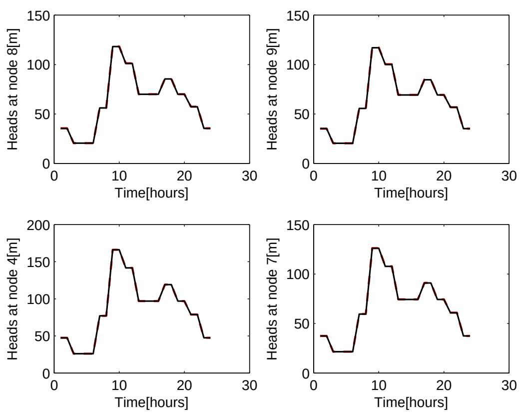
Pipe ID	L(m)	D(mm)	Node	Demand(m^3/s)
1	400	200	1	
2	100	300	2	0.05
3	500	200	3	0.03
4	700	300	4	0.02
5	700	200	5	0.03
6	400	300	6	0
7	400	250	7	0.08
8	100	300	8	0.09
9	900	300	9	0.09
10	500	300	10	0.09
11	900	300	11	0.08
12	700	100	12	0.06
13	100	200		
14	1000	200		
15	300	300		
16	800	200		
17	700	150		

Table 3.3: Reservoir heads

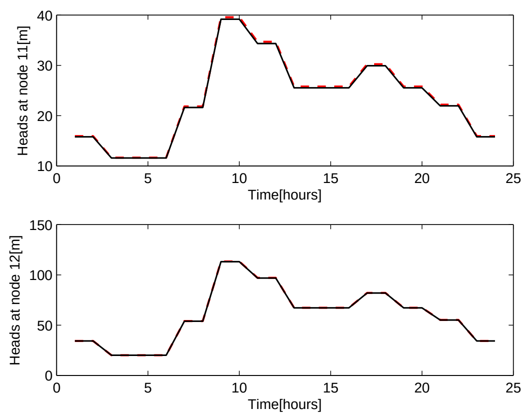
Time	1	2	3	4	5	6	7	8	9	10	11	12
	53.6	53.6	28.9	28.9	28.9	28.9	87.9	87.9	190.9	190.9	162.5	162.5
Time	13	14	15	16	17	18	19	20	21	22	23	24
	110.8	110.8	110.8	110.8	136.6	136.6	110.8	110.8	89.9	89.9	53.6	53.6

3.3.2 Case study- simulations of water distribution systems

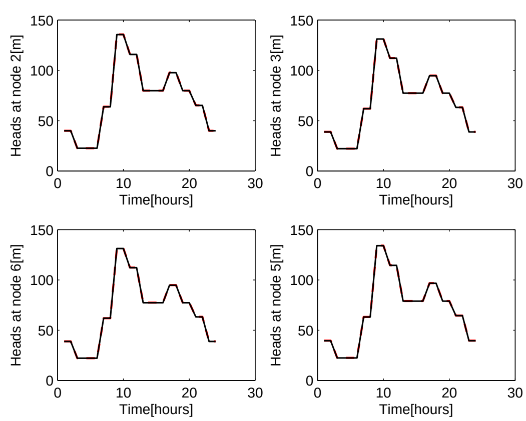
We consider a water distribution system investigated in [4]. The system consists of 17 pipes, 12 nodes, and one reservoir. Data of the system and 24 reservoir heads (node 1) are given in Table 3.2 and Table 3.3, respectively. To evaluate the accuracy of the smooth head loss, the Newton- Raphson method described above is employed to solve the flows and heads of the system (38 variables) in which the developed smooth head loss is used to calculate the pipe head loss. To solve the linear systems, we use a linear sparse solver provided in [109]. The corresponding results (flows and nodal heads) are compared with the ones resulted by simulating the water distribution system with the same data using EPANET 2 [58] (where the non-smooth Darcy-Weisbach equation is used). It can be seen in Fig. 3.4 and 3.5 that the flows and heads obtained from using the smooth head loss are almost the same with those obtained from using the non-smooth Darcy-Weisbach equation in EPANET 2 [58].



(a)



(b)



(c)

Figure 3.4: The dotted red lines are heads using the smooth head loss, the solid black lines are heads using the non-smooth Darcy-Weisbach from EPANET 2

Now we consider the EXNET system in [2]. This water distribution system is one of the largest scale systems with 1892 nodes and 2350 links. The smooth head loss is used for the pipe head loss computation. The heads of reservoirs 3001, and 3002 are fixed to 91.4246 and 73.486 m ,respectively. Similarly, the link flows and nodal heads (4242 variables) resulted by using the smooth head loss and the Newton-Rapshson method are compared with those resulted from simulating the EXNET by EPANET 2 are compared. The absolute and relative discrepancies of flows and heads are given in Fig. 3.6. It can be seen in the figure that the use of the smoothed head loss model results in very high accurate heads. In particular, the largest absolute discrepancy of nodal heads is smaller than 0.5 (m), and the largest relative discrepancy of heads is 3.5%. As for the flows, the largest relative discrepancy is 5% and the most of them is less than 2.5% for flows larger than 10 (l/s). These correspond to the fact that the largest absolute discrepancy is 3 (l/s) and most of them is less than 1 (l/s). More importantly, the flows through the most pipes (i.e., pipes with large diameters) have small relative and absolute discrepancies of flows and heads. From the simulation comparisons of the two case studies using the smooth head loss, it can be concluded that the use of smooth head loss in [8] is accurate enough and suitable for the formulation of nonlinear continuous optimization for pressure managements and operations of water distribution systems.

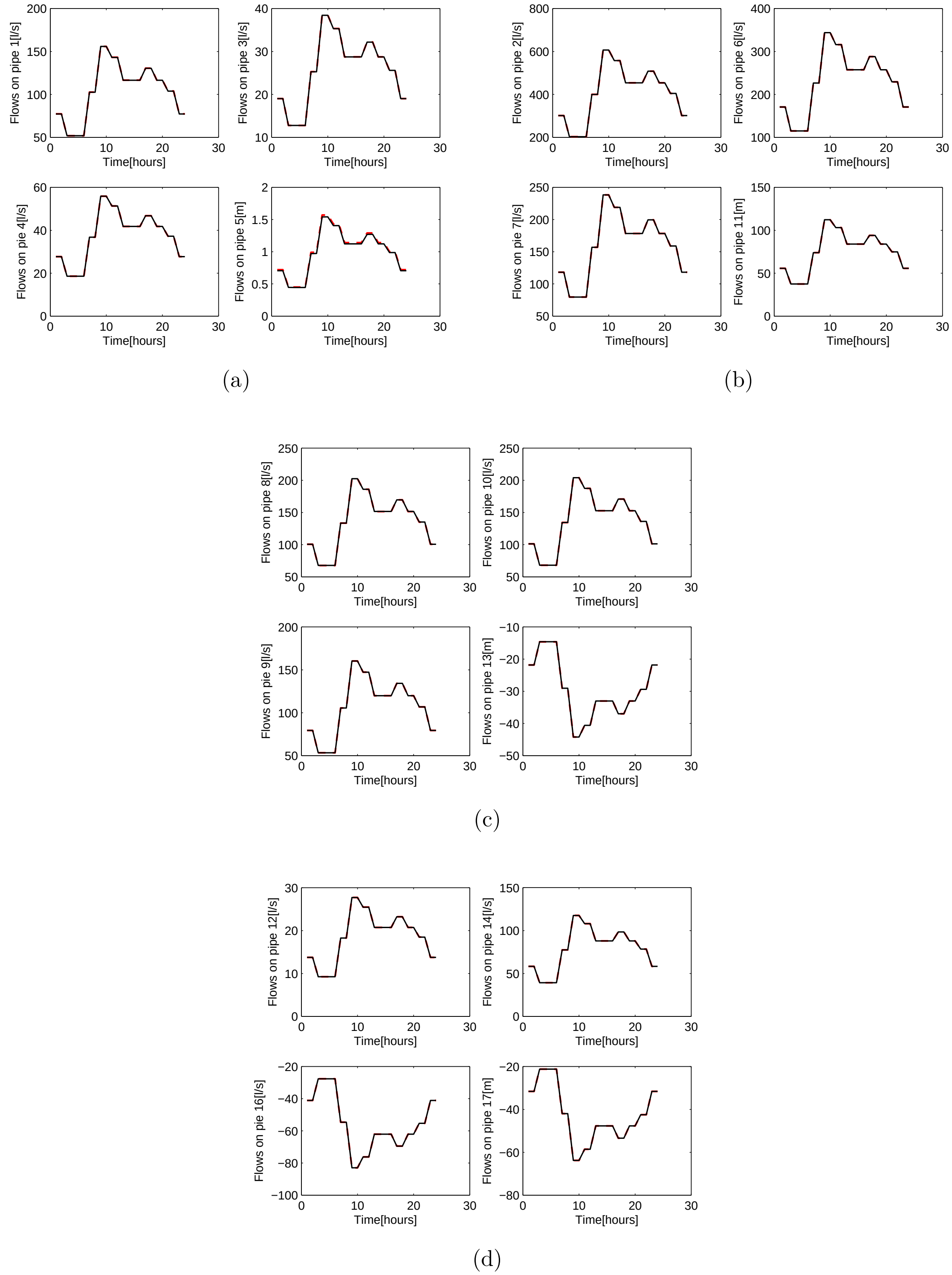
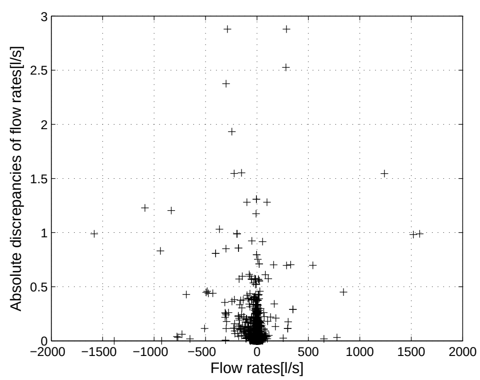
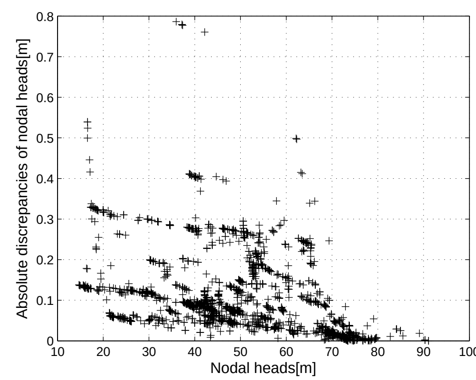


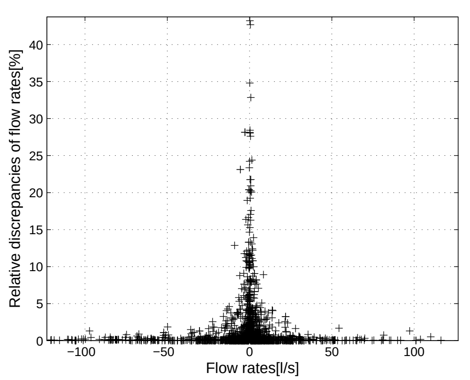
Figure 3.5: The dotted red lines are flows using the smooth head loss, the solid black lines are flows using the non-smooth Darcy-Weisbach from EPANET 2



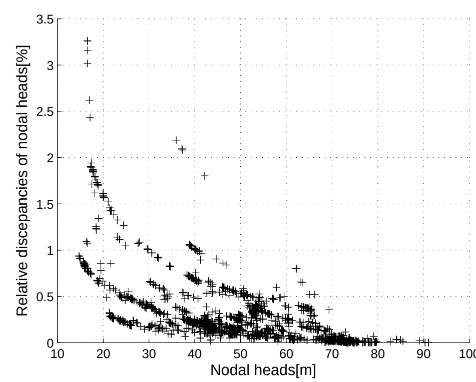
(a) Pipe flows



(b) Nodal heads



(c) Pipe flows



(d) Nodal heads

Figure 3.6: Relative and absolute discrepancies of pipe flows and nodal heads with K_s=0.35, a=1.e-6

Chapter 4

Optimal Localization of Pressure Reducing Valves Using a Reformulation Approach

Leakage reduction represents one of the most challenging tasks in managing water distribution systems(WDSs). An effective way to leakage reduction is to carry out network operational pressure management through optimizing locations and regulations for pressure reducing valves (PRVs) and system pressures. This leads to a mixed-integer nonlinear program (MINLP) with a large number of binary variables which make it difficult to solve by an available software package. In this chapter, instead of directly solving the MINLP problem, we reformulate it to a mathematical program with complementarity constraints which can be efficiently solved by available NLP algorithms. The binary variables are replaced by continuous ones with complementarity constraints to be satisfied by a penalization scheme. To improve the quality of the solution and also to accelerate the convergence, in each relaxed NLP the results of the binary variables are rounded to binary values with which the NLP problem is solved again to achieve a MINLP solution. The final solution will be determined by the best one among the MINLP solutions. The results from two case studies reveal new and better combinations of PRVs as compared with those given in the literature.

4.1 Introduction

The amount of water leakage loss in water distribution systems, mainly due to the deterioration of pipes and high values of operating pressure, is one of the major concerns of municipalities [32]. To reduce water leakage, four basic methods in leakage management are proposed which are pipeline and assets management, pressure management, speed and quality of repairs, and active leakage control [21, 32, 46]. Among which pressure management is one of the most effective approaches to leakage reduction as it influences the frequency of new leaks and the flow rates of all leaks and bursts [30, 32].

Pressure regulations in WDSs can be accomplished in several means such as installing isolated valves to subdivide the network into smaller sectors or districts having different pressure regimes and/or installing control or pressure reducing valves [32]. In this chapter, we address the optimal localization of pressure reducing valves (PRVs) in WDSs so as to minimize the excessive pressure and thus leakage flows. The optimal localization of PRVs is formulated as a mixed integer nonlinear programming problem (MINLP) since binary variables are introduced to each link to indicate whether or not PRVs are placed on the links. It is obvious that for a large scale WDS with thousand pipes, the formulated MINLP become large and it is difficult to be solved by available MINLP algorithms. In addition, the MINLP model has to consider multiple demand scenarios to ensure that optimized locations of PRVs account all operating scenarios. This makes the MINLP even more difficult to solve.

MINLP algorithms rely on either solving NLP sub-problems based on a branch and bound method or solving NLP and MILP based on a decomposition method [110]. Due to the challenges from treating integer variables and handling nonlinear non-convex equations, the solution of a large-scale MINLP problem suffers from a lack of robustness, reliability, and efficiency [50]. Alternatively, continuous reformulation approaches reformulate MINLP as NLP with complementarity constraints [49, 50, 111] which is then solved by a regularization approach such as smoothing, relaxation, and penalization methods [112, 113]. A MINLP problem for the process synthesis was reformulated into a MPCC in [50]. It is then solved by subsequently tightening the Fischer- Burmeister function to enforce relaxed binary variables to obtain binary values. In [39], the MPCC approach was applied to solve MINLP problems by solving sequence of NLPs with relaxation (e.g., tightening the Fischer- Burmeister function) and penalization (e.g., increasing the penalty parameter value) schemes. Numerical experiments with the both schemes carried out for a selection of MINLP problems in MINLPlib have demonstrated that the penalization scheme is slightly superior than the relaxation scheme. Although many studies have been made on the development of reformulation and regularization approaches and these approaches have been applied in many engineering fields, no application can be found to the optimal localization of PRVs for managing pressures in WDSs.

In this chapter, the MINLP problem for PRV localization is reformulated as a mathematical program with complementarity constraints (MPCC). The MPCC is solved in a sequence of NLPs with an increasing penalty parameter. In addition, a novel scheme to round the relaxed solutions of each NLP to binary values of the binary variables is proposed and the rounding ensures the feasibility of the original MINLP. This scheme enables to find potential local solutions of the MINLP during solving the sequence of NLPs. As a result, the quality of the solution can be improved and the convergence of the algorithm can be accelerated. Two case studies are taken to demonstrate the effectiveness of the proposed approach. Comparing with the solutions by a MINLP solver, optimal localization problems of PRVs for large-scale WDSs can be solved by the proposed reformulation approach with higher robustness and in less computation time. Comparing with the solutions of the case studies by the meta-heuristic methods reported in the literature, we found more accurate solutions with higher reduction of system pressure and of leakage amount.

The remainder of this chapter is organized as follows. In section 4.2 the MINLP for PRV localization considering multiple demand patterns and leakage terms is formulated. In section 4.3 we present a reformulation of the MINLP by mathematical programming complementarity constraints (MPCC) with a penalization method. In section 4.4 a new scheme to relate the rounded solution of NLP to that of MINLP and a computation framework is introduced. Two case studies are carried out in section 4.5 and conclusions are given in section 4.6.

4.2 Problem formulation and solution approach

In this section we will formulate a MINLP problem for optimal localization of PRVs for the pressure management of WDSs. PRVs should be placed on proper links to reduce the downstream heads so that the system pressure is minimized. For unidirectional flows, a binary variable is needed for each link to represent whether a valve is placed on the link or not. We consider bidirectional flows which require two binary variables ($v_{i,j}$ and $v_{j,i}$) for each link corresponding to the forward and backward flows, respectively. The placement of a PRV increases the head loss across the link and thus the downstream head will be reduced. The head loss on a link with flow direction i to j for load pattern k can be expressed by [35, 114].

$$\Delta H_{i,j,k} \leq H_{i,k} - H_{j,k} \leq \Delta H_{i,j,k} + M_{i,j} v_{i,j} \tag{4.1}$$

where the pipe head loss $\Delta H_{i,j,k}$ can be computed either by the Hazen-Williams equation

$$\Delta H_{i,j.k} = \frac{10.67 L_{i,j}}{D^{4.87}} \left(\frac{Q_{i,j,k}}{C} \right)^{1.852} \tag{4.2}$$

or by the Darcy-Weisbach equation

$$\Delta H_{i,j,k} = \frac{8 L f}{g \pi^2 D^5} \left| Q_{i,j,k} \right| Q_{i,j,k} \tag{4.3}$$

The friction factor f in (4.3) is calculated from the Colebrook-White equation

$$\frac{1}{\sqrt{f}} = 2 \log \left(\frac{2.51}{\mathrm{Re} \sqrt{f}} + \frac{\varepsilon}{3.71 D} \right) \tag{4.4}$$

where L, D and C are the length, diameter and Hazen-William coefficient of pipe, respectively; ε and Re in (4.4) are the pipe roughness coefficient and Reynolds number,

respectively.
The difference between (4.2) and (4.3) lies in the fact that (4.2) is a simple and smooth model with a lower accuracy, while the accuracy of (4.3) is much higher but it is more complicated and non-smooth. One smooth form of (4.3) was proposed in [8] allowing the use of the Darcy-Weisbach equation in the NLP formulation. In this work, we will use both equations in the case studies for the head loss computation. To formulate the optimal localization problem for PRVs, we consider a WDS with N_n nodes, N_p pipes, and N_L demand patterns.
The optimization problem is defined as the minimization of the total excessive pressure under multiple demand patterns.

$$\min F = \sum_{i=1}^{N_n} \sum_{k=1}^{N_L} \left(H_{i,k} - H_i^L \right) \tag{4.5}$$

subject to the continuity equation at node i for demand pattern k

$$\sum_{j,k} Q_{j,i,k} - \sum_{j,k} Q_{i,j,k} - d_{i,k} - l_i = 0 \tag{4.6}$$

where $d_{i,k}$ represents demand of node i at pattern k; $Q_{j,i,k}$, $Q_{i,j,k}$ denote the flows of the forward ($j \to i$) and backward ($i \to j$) flow directions, respectively. Since only one flow direction should be active and only one valve can be placed on a link, following constraints are introduced

$$0 \leq Q_{j,i,k} \leq Q^U \tag{4.7}$$

$$0 \leq Q_{i,j,k} \leq Q^U \tag{4.8}$$

$$0 \leq v_{i,j} + v_{j,i} \leq 1 \tag{4.9}$$

The head loss constraints of a link described by (4.1) should be held if the flow is in the forward direction, whereas they should be relaxed if the flow is in the backward direction. Therefore, the head loss constraints in the forward direction (the backward direction can be formulated in the similar way) are expressed by [35, 115]

$$Q_{i,j,k} \left(H_{i,k} - H_{j,k} - \Delta H_{i,j,k} \right) \geq 0 \tag{4.10}$$

$$H_{i,k} - H_{j,k} - \Delta H_{i,j,k} - M_{i,j} v_{i,j} \leq 0 \tag{4.11}$$

In addition, the head constraints should be satisfied,

$$H^L \leq H_{i,k} \leq H^U \tag{4.12}$$

Moreover, if N_v pressure reducing valves are to be placed in the system, there should be

$$\sum_{i,j} \left(v_{i,j} + v_{j,i} \right) = N_v \tag{4.13}$$

The leakage amount associated to node i is calculated by [1, 32] .

$$l_i = C_L L_{t,i} p_i^{\gamma} \tag{4.14}$$

where

$$L_{t,i} = 0.5 \sum_j L_{i,j} \tag{4.15}$$

In (4.14) C_L is the discharge coefficient of the orifice and γ is the pressure exponent [1]. The big $M_{i,j}$ number associated to link i, j is chosen so that the head loss dropped across the link can lower the pressure at downstream node j to the target pressure (or the minimum allowable pressure). For this reason, we can determine its value by

$$M_{i,j} = H^m - H_j^L \tag{4.16}$$

where H^m is the maximum head and H_j^L the minimum allowable head at node j. The above MINLP problem for optimal PRV localization can be described in a general form

$$\min f(\mathbf{x}, \mathbf{y}) \tag{4.17a}$$

subject to

$$\mathbf{g}(\mathbf{x}) = \mathbf{0} \tag{4.17b}$$

$$\mathbf{h}(\mathbf{x}, \mathbf{y}) \geq \mathbf{0} \tag{4.17c}$$

$$\mathbf{y} = \{0, 1\}^{2N_p} \tag{4.17d}$$

$$\mathbf{x}^U \geq \mathbf{x} \geq \mathbf{x}^L \tag{4.17e}$$

where $\mathbf{x} = (\mathbf{Q}, \mathbf{H})$ represents the vector of continuous variables and $\mathbf{y} = (\mathbf{v}_{i,j}, \mathbf{v}_{j,i})$ the vector of binary variables, respectively; f, $\mathbf{g}$, and $\mathbf{h}$ denote the objective function, equality constraints, and inequality constraints. The number of continuous and binary variables is $(2N_p+N_n)N_L$ and $2N_p$, respectively.

4.3 Reformulation of the MINLP as MPCC

Now we relax the MINLP (4.17) into a NLP problem in which the binary variables $y_i \in \{0, 1\}^{2N_p}$ are treated as continuous ones $0 \leq y_i \leq 1$. To obtain a binary solution, we need to enforce that for each i ($i = 1, ..., 2N_p$) one of the bounds is active (such that $y_i \in \{0, 1\}^{2N_p}$). This calls for the complementarity condition [39, 111].

$$0 \leq y_i \perp 1 - y_i \geq 0 \tag{4.18}$$

Replacing the binary constraints in (4.17) by the complementarity constraints in (4.18) leads to a MPCC problem [39, 49, 111].

$$\min f(\mathbf{x}, \mathbf{y}) \tag{4.19a}$$

subject to

$$\mathbf{g}(\mathbf{x}) = \mathbf{0} \tag{4.19b}$$
$$\mathbf{h}(\mathbf{x}, \mathbf{y}) \geq \mathbf{0} \tag{4.19c}$$
$$0 \leq y_i \perp 1 - y_i \geq 0 \tag{4.19d}$$
$$\mathbf{x}^U \geq \mathbf{x} \geq \mathbf{x}^L \tag{4.19e}$$
$$i = 1, ..., 2N_p \tag{4.19f}$$

To solve (4.19), we use a penalization scheme, i.e. the complementarity constraints in (4.19) will be expressed as a penalty term in the objective function [112, 113, 116]. In this way, (4.19) becomes

$$\min f(\mathbf{x}, \mathbf{y}) + \mu \Psi (y_i, 1 - y_i) \tag{4.20a}$$

subject to

$$\mathbf{g}(\mathbf{x}) = \mathbf{0} \tag{4.20b}$$
$$\mathbf{h}(\mathbf{x}, \mathbf{y}) \geq \mathbf{0} \tag{4.20c}$$
$$1 \geq y_i \geq 0 \tag{4.20d}$$
$$\mathbf{x}^U \geq \mathbf{x} \geq \mathbf{x}^L \tag{4.20e}$$
$$i = 1, ..., 2N_p \tag{4.20f}$$

where μ is a penalty parameter; $\Psi(y_i, 1 - y_i)$ can be either [39]

$$\Psi(y_i, 1 - y_i) = \sum_{i=1}^{2N_p} y_i (1 - y_i) \tag{4.21}$$

or

$$\Psi(y_i, 1 - y_i) = \sum_{i=1}^{2N_p} \left(1 - \sqrt{y_i^2 + (1 - y_i)^2}\right) \tag{4.22}$$

In this work we use (4.21). It can be seen that (4.20) is a continuous NLP problem which can be efficiently solved by an available NLP solver. The solution strategy of a MPCC is given in the appendix B.2

Using the MPCC approach, a sequence of NLPs with an increasing value of the penalty parameter will be solved. The corresponding solutions are called stationary points $\left(x^k, y^k\right)$ of NLP(μ^k) and $\left(x^k, y^k\right) \rightarrow (\overline{x}, \overline{y})$ as $\mu^k \rightarrow +\infty$, which is a limit point or solution of MPCC [112, 113]. In the MPCC computation framework, instead of driving $\mu^k \rightarrow +\infty$, the penalty parameter μ^k needs to increase to a large enough value at which the stopping criterion is satisfied [112, 113].

Unfortunately, MPCC problems are in general non-convex and thus a stationary point depends on the initial guess. Therefore, there may be several sequences of stationary points $\left(x^k, y^k\right)$ which lead to different limit points $(\overline{x}, \overline{y})$ for the MPCC. Since theoretically it is necessary that $\mu^k \to +\infty$, i.e. a lot of NLPs have to be solved. This will leads to large computation expense. Our question now is how to accelerate the search procedure by utilizing the available stationary solutions during the NLP sequence.

4.4 A new rounding scheme for finding feasible MINLP solutions and the computation framework

Locations of PRVs should be on links at which they can lower the downstream link pressures. By using simulation studies, Liberatore and Sechi in [33] proposed to determine a set of link candidates for PRV locations based on comparing the nodal pressure with a pre-defined reference pressure value. Links connected to nodes with pressures higher than the reference pressure value can be considered for PRV placements. In the same manner, nonzero values of $v_{i,j}$ or $v_{j,i}$ can also be considered as link candidates for PRV locations.

In fact, a nonzero $v_{i,j}$ or $v_{j,i}$ is equivalent to the effect of an increase of the roughness of a pipe or a decrease in the Hazen-Williams coefficient, since both increase the head loss across the link. The links with a larger roughness than real ones (i.e. nonzero $v_{i,j}$ or $v_{j,i}$) can be considered for PRV locations [1]. Using the MPCC approach described in section 4.3, the solution of each relaxed NLP problem provides the information about the links and their directions for PRV placements. Therefore, the links associated with nonzero $v_{i,j}$ or $v_{j,i}$ are candidates for PRV locations.

As we increase the penalty parameter μ^k, the number of link candidates will decrease and it will be equal to the defined number of PRVs (N_v) as μ^k approach to a sufficiently large value. Our question now is that can the solution of the MINLP problem be found before a large enough penalty parameter is reached?. This can be answered by considering the feasibility of constraints if we round fractional values $v_{i,j}$ (or $v_{j,i}$) to 1 or 0.

For a set of N link candidates with nonzero values $v_{i,j}$ or $(v_{j,i})$, we have

$$0 \leq H_i - H_j - \Delta H_{i,j} - M_{i,j} v_{i,j} \leq 0; i, j = 1, ..., N \tag{4.23a}$$

If a set of N_v nonzero values, chosen from N link candidates, is rounded to 1, the constraints (4.23a) representing a PRV on the link becomes

$$0 \leq H_i - H_j - \Delta H_{i,j} - M_{i,j} \leq 0; i, j = 1, ..., N_v \tag{4.23b}$$

while others nonzero values are rounded to 0, for which the (4.23a) becomes

$$0 \leq H_i - H_j - \Delta H_{i,j} \leq 0 \tag{4.23c}$$

From (4.23a), (4.23b) and (4.23c) we can conclude there exist $\mathbf{Q}$ and $\mathbf{H}$ satisfying the constraints of the MINLP (4.17) after rounding $v_{i,j}$ and $v_{j,i}$ and the rounded values

is one feasible solution of the MINLP (4.17). The first reason is that the constraints (4.23b) cover the constraints (4.23a), so that if the constraints (4.23a) are satisfied, (4.23b) will be satisfied. The second reason is due to the fact that solutions of $\mathbf{Q}$ and $\mathbf{H}$ by solving the equations (4.6) and (4.23c) satisfy the MINLP problem in the case of no PRVs. As a result, the MINLP problem with the set of constraints (4.23c), (4.23b), and (4.6) has a feasible solution. With this rounding scheme, a solution for optimal PRV locations will be found in the sense of the approach of Liberatore and Sechi in [33] and the approach of Ajauro et al in [1]. This means that the solution is determined from the link candidates. The difference between our approach and these approaches lies in the fact that the link candidates are found during solving a sequence of relaxed NLPs, while the mentioned approaches use heuristic algorithms.
To round the nonzero values of $v_{i,j}$ and $v_{j,i}$, we propose the following strategy

$$v'_{i,j} = \begin{cases} 1 & \text{if} \quad v_{i,j} \geq \delta \\ 0 & \text{if} \quad v_{i,j} < \delta \end{cases} \quad \text{and} \quad v'_{j,i} = \begin{cases} 1 & \text{if} \quad v_{j,i} \geq \delta \\ 0 & \text{if} \quad v_{j,i} < \delta \end{cases} \tag{4.24}$$

and

$$\sum_{i,j} \left(v'_{i,j} + v'_{j,i} \right) = N_v \tag{4.25}$$

where $\delta > 0$ is a predefined threshold value. It means the nonzero values $\mathbf{y} = (\mathbf{v}_{i,j}, \mathbf{v}_{j,i})$ and rounded values $\mathbf{y'} = \text{round}\,(\mathbf{y}) = (\mathbf{v'}_{i,j}, \mathbf{v'}_{j,i})$. In addition, a limit point is determined if the following condition is satisfied [113].

$$\sqrt{\sum_{i,j} \left((\min\,(v_{i,j}, 1 - v_{i,j}))^2 + (\min\,(v_{j,i}, 1 - v_{j,i}))^2 \right)} \leq \theta \tag{4.26}$$

where $\theta > 0$ is a convergence threshold which we chose as 0.001. In our approach, local solutions are searched during solving a sequence of NLPs with rounded values of the binary variables from (4.24), while the limit point will be found when (4.26) is satisfied. It can be seen from (4.24) that, as $\delta \to 0$, the solution obtained by solving the NLP will be a limit point.

Based on the rounding scheme and the reformulation approach described in Section 4.3, we propose the computation framework as shown in Table 4.1 for solving optimal PRV localization problems. The computation starts with initial parameters for the optimization problem such as the number of valves (N_v), the coefficient value (α), and the initial penalty parameter (μ^0). μ^0 is chosen as a fraction (i.e. $\beta = [0.05 \;\; 0.1]$) of the objective function value of the NLP problem (4.20) solved with $\mu = 0$ (z^0_{NLP}). The solution of MPCC depends on how the penalty parameter is updated [113]. However, there is no available strategy in the literature to update this parameter. In our implementation, we at first use $\alpha = 1.1$ for updating the penalty parameter. When the first local solution is found, we use $\alpha = [1.0001 \;\; 1.001]$. Initial guesses for the relaxed NLPs are randomly generated.
The Epanet Toolkit [106] is used to access the data and structure of the water distribution system and formulate the NLP problem. The NLP solver IPOPT [117] is used to

Table 4.1: The computation framework

Initialization: N_v, α,δ,$z_{best} = +\infty$;$k = 0$, $maxIter$.
Solve the relaxed NLP with $\mu = 0$ gives the objective function value z^0_{NLP}.
Assign $\mu^0 = \beta z^0_{NLP}$.
repeat
If the condition (4.25) is satisfied then
If $z^k_{NLP} < z_{best}$ then
solve the NLP problem (4.20) with the rounded values of $v_{i,j}$ and $v_{j,i}$, obtain the objective function value z; $z_{best} = min(z, z_{best})$
Update the iteration $k = k + 1$.
Update penalty parameter $\mu^k = \alpha\mu^{k-1}$.
Generate random initial guesses for NLP(μ^k).
Solve the NLP(μ^k) to obtain the objective function value z^k_{NLP}.
until $k = maxIter$.

solve the relaxed NLP problem. The brief description of IPOPT is given in the appendix B.1.

4.5 Case studies

4.5.1 Case study 1: PRV localization for a benchmark WDS

Optimal PRV localization is carried out for a well-known water distribution system, as shown in Figure 4.1, which was studied by [6, 7, 31, 32].The system comprises 22 nodes, 3 reservoirs, and 37 links. The coefficients relating the leakage per unit length of the links to the service pressure and leakage exponent are $C_L = 10^{-5}$ and $\gamma = 1.18$, respectively. The constant heads at reservoir nodes 23, 24, and 25 are 54.66 (m), 54.60 (m), and 54.55(m), respectively, as taken from Nicolini and Zovatto in [32]. At first, we consider three demand patterns (i.e. with three demand multipliers defined as 0.6, 1.0, and 1.4). The minimum pressure required at all nodes in the WDS is 30.0(m). Five cases with numbers of valves ranging from 2 to 6 are considered. The resulting MINLP problem contains 288 continuous variables, 74 binary variables, and 288 constraints.

The optimal locations of PRVs and their pressure settings obtained from our approach are passed to EPANET 2 [106] which calculates the excessive pressure and leakage amount. In this way, we can compare our results with those given in the literature.

It can be seen in Table 4.2 and 4.3, in the case of 2 PRVs our approach finds the link 11 and 20 which are the same as those found by Nicolini and Zovatto in [32]. In the

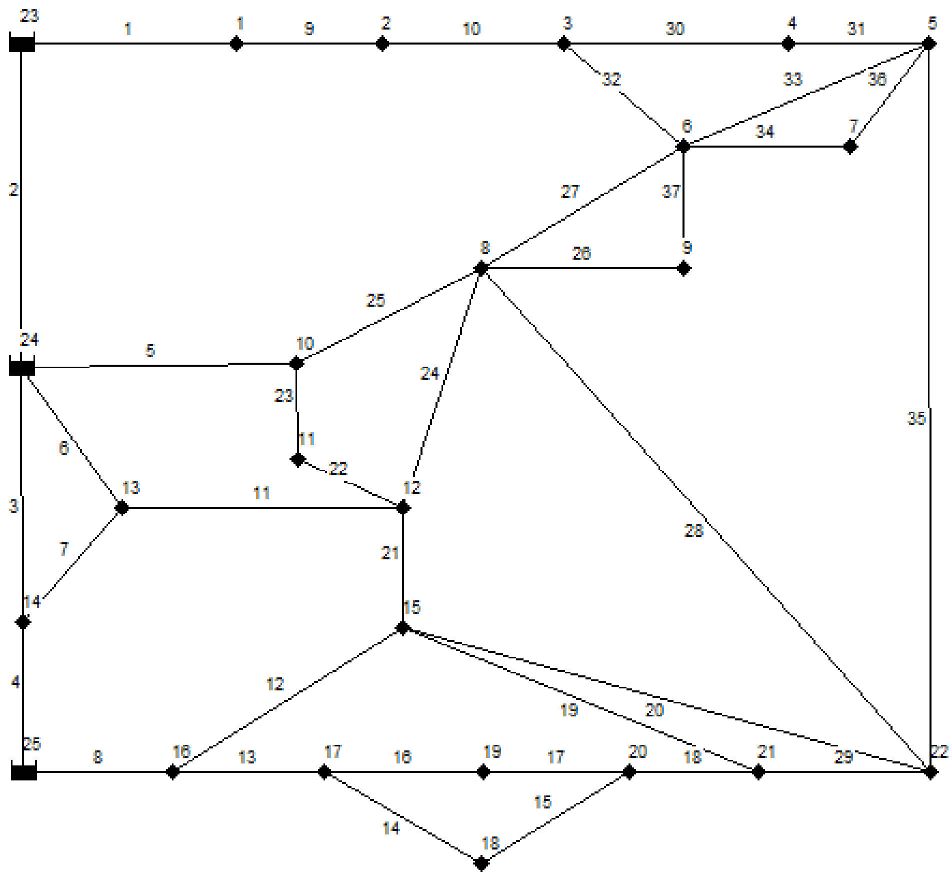


Figure 4.1: A WDS benchmark for PRV localization [6, 7]

Table 4.2: Optimal PRV locations for the WDS benchmark with 3 demand patterns

Reformulation approach			Nicolini and Zovatto [32]	MINLP	
No.of PRVs	LinkIDs	CPU time[s]	LinkIDs	LinkIDs	CPU time[s]
1	11	9.57	11	11	8.67
2	11,20	16.00	11,20	11, 20	237.29
3	11,20,21	26.26	1,11,20	11,20,21	505.349
4	1,11,20,21	20.03	1,11,20,21	1,11,20,21	1156.64
5	1,11,8,20,29	21.93	1,11,20,21,27	1,11,19,20,21	3471.02

case of 3 PRVs, the best locations from our approach are on the links of 11, 20, and 21, which results in an average excessive pressure of 2.467(m) and an average leakage amount of 23.60(l/s). Nicolini and Zovatto in [32] reported the best locations are on the links of 1, 11, and 20 with the average of excessive pressure of 3.187(m) and the average leakage amount of 23.39(l/s). The solution from our approach leads to a higher reduction of the excessive pressure, while the solution by Nicolini and Zovatto in [32] causes a higher reduction of the leakage amount. The difference between both solutions may lie in the fact that our approach minimizes the system excessive pressure, while the approach by Nicolini and Zovatto in [32] minimized the system leakage amount. In the case of 4 PRVs, the best PRV locations found are on the links of 1, 11, 20 and 21 which are the same as reported by Nicolini and Zovatto in [32]. However, the average excessive pressure and leakage amount by our approach are 1.807(m) and 22.89(l/s), respectively, while they are 2.013(m) and 22.98(l/s) in [32]. For this case, our solution leads to a higher reduction of both the excessive pressure and the leakage amount.

In the case of 5 PRVs, our approach finds the optimal locations of PRVs on the links of 1, 8, 11, 20, and 29 with an average excessive pressure and leakage amount as 1.647 (m), and 22.73(l/s), respectively. The optimal PRV locations by Nicolini and Zovatto [32] are on the links of 1, 11, 20, 21, and 27 which result in an average excessive pressure of 1.873 (m) and 22.89 (l/s) of leakage amount. The pressure settings $(p_{j,1}, p_{j,2}, p_{j,3})$ for the three demand patters in the case of 5 PRVs are given in Table 4.4. It can be seen that the PRVs located on the links of 20 and 29 are 100% closed for all demand patterns, while the PRVs on the links of 1, 8, and 11 operate with appropriate openings (i.e., the PRVs maintain their pressure settings on their downstream nodes). The penalty parameter values, with which the solution obtains the lowest objective value, are given in Table 4.5. This means that the computation does not needs a large number of iterations for solving the relaxed NLP problem. Moreover, the CPU time for solving each of localization problems is about 26(s) on an Intel (R) Core (TM) 3.40GHz 2.99GB RAM desktop, as shown in Table 4.2.

For the purpose of a comparison, we also solved this localization problem by directly solving the MINLP problem using the BONMIN solver [118] in GAMS [119]. The results are also shown in Table 4.2 and 4.3. It can be seen that for the cases of 2, 3, and 4 PRVs, the locations are the same as those by our reformulation approach. However, it takes much longer computation time by directly solving the MINLP problem. In particular, in the case of 5 PRVs, it takes 3471.02(s) and converges to a lower quality solution with the average of excessive pressure of 1.990(m).

Now we consider the localization problem for the WDS with 24 demand patterns and 24 reservoir water heads. The demand patterns and reservoir heads in a time horizon of 24 hours are given in Table 4.6.

This case was studied by Araujo et al in [1] in which the so-called throttle control valves (TCVs) were used to manage the system pressure, using a two-phase GA approach. In principle, both TCVs and PRVs are controlled by adjusting their resistances or head losses [106]. Thus we can compare the results from our approach with those given in [1]. For 24 demand patterns, the MINLP problem is formulated with 2304 continuous

Table 4.3: Average excessive pressure and leakage from the WDS benchmark with 3 demand patterns

	Reformulation approach		Nicolini and Zovatto [32]		MINLP	
No.of PRVs	Average-leakage [l· s^{-1}]	Average-excessive pressure [m]	Average-leakage [l· s^{-1}]	Average-excessive pressure [m]	Average-leakage [l· s^{-1}]	Average-excessive pressure [m]
1	24.55	3.939	24.70	4.013	24.55	3.939
2	23.81	2.872	24.08	3.187	23.81	2.872
3	23.60	2.467	23.39	2.501	23.60	2.467
4	22.89	1.807	22.98	2.013	22.89	1.807
5	22.73	1.647	22.89	1.873	22.97	1.990

Table 4.4: Operations of 5 PRVs

Pressure settings	1	8	11	20	29
$p_{j,1}$	30.03	30.10	30.60	Closed	Closed
$p_{j,2}$	30.05	30.26	31.75	Closed	Closed
$p_{j,3}$	30.08	30.39	34.45	Closed	Closed

Table 4.5: .Penalty parameter values in different cases with 3 demand patterns

No. of PRVs	Penalty parameter values	Number of iterations
1	126.48	19
2	129.76	31
3	76.13	19
4	52.94	22
5	42.88	24

Table 4.6: Data for the demand patterns and reservoir water levels at nodes 23, 24, and 25 [1]

Time	1	2	3	4	5	6	7	8	9	10	11	12
Fc	0.61	0.61	0.41	0.41	0.41	0.41	0.81	0.81	1.23	1.23	1.13	1.13
23	55.2	55.3	55.5	55.6	55.7	55.8	55.9	56.0	55.7	55.4	55.2	55.1
24	55.2	55.3	55.3	55.4	55.4	55.5	55.5	55.5	55.3	55.2	55.0	54.8
25	55.0	55.1	55.2	55.3	55.4	55.4	55.5	55.5	55.5	55.0	54.8	54.7
Time	13	14	15	16	17	18	19	20	21	22	23	24
Fc	0.92	0.92	0.92	0.92	1.03	1.03	0.92	0.92	0.82	0.82	0.61	0.61
23	54.9	54.7	54.6	54.6	54.5	54.5	54.6	54.7	54.8	54.9	55.0	55.2
24	54.8	54.8	54.7	54.6	54.5	54.7	54.7	54.7	54.7	54.8	54.9	55.0
25	54.5	54.4	54.3	54.1	54.0	54.0	54.2	54.3	54.5	54.6	54.8	54.9

variables, 74 binary variables, and 2376 constraints. The PRV locations with respect to different numbers of PRVs are shown in Table 4.7. It can be seen that the links of 1, 5, 8, 11, 20, 21, 29, and 31 are determined for possible PRV locations, which are the same as the locations determined by Araujo et al in [1]. However, the PRV locations for the specified number of PRVs are different. In the case of 2 PRVs, our approach found links 1, 11 as locations which are the same as those found by Araujo et al in [1]. With these PRV locations, the decreases of the average leakage amounts by both approaches are 4.5(l/s). The locations of 3, 4, 5, and 6 PRVs by our approach are different to those by Araujo et al in [1]. As shown in Table 4.8, in these cases our approach leads to a higher reduction of the average leakage amount.
Figure 4.2 shows the dynamic leak flows for the specified number of PRVs in 24 hours by our approach. Table 4.8 shows the decreases of average leakage amounts as compared with the case of no PRVs. In particular, the case of 6 PRVs reduces an average leakage of 5.77(l/s), followed by 5.7(l/s) using 5 PRVs, 5.50(l/s) using 4 PRVs, 4.77(l/s) using 3 PRVs, and 4.53(l/s) using 2 PRVs, respectively. As shown in Table 4.7, the CPU time for solving the problems with 24 demand patterns is higher than in the case of 3 demand patterns shown in Table 4.2. And the penalty parameter values, at which the solutions are found, are also higher in comparison to those in the case of 3 demand patterns, due to the higher number of NLP iterations, as shown in Table 4.9.

Using the BONMIN solver [118] in GAMS [119], we also solved the MINLP problems with 24 demand patterns. However, we could only obtain solutions in the case of 1 and 2 PRVs. With more than 2 PRVs, the computation failed to converge.

Table 4.7: Optimal PRV locations with 24 demand patterns

Reformulation approach				Araujo et al [1]
No.of PRVs	LinkIDs	Total excessive pressure [m]	CPU time[s]	LinkIDs
2	1,11	1721.89	428.57	1,11
3	11,20,21	1327.98	899.47	11,21,29
4	1,11,20,29	984.13	651.8	1,8,11,20
5	1,11,20,21,29	840.01	350.49	1,8,11,21,29
6	1,11,20,21,29,31	798.53	819.14	1,5,11,8,20,21

Table 4.8: Comparison of the average decrease in leakage amount with 24 demand patterns

Reformulation approach		Araujo et al [1]
No.of PRVs	Average decrease-leakage[l· s^{-1}]	Average decrease-leakage[l· s^{-1}]
2	4.53	4.5
3	4.77	4.0
4	5.50	5.1
5	5.70	4.7
6	5.76	5.2

Table 4.9: Penalty parameter values in different cases with 24 demand patterns

No. of PRVs	Penalty parameter values	Number of iterations
2	1763.39	46
3	782.98	33
4	1404.11	29
5	434.23	28
6	440.78	65

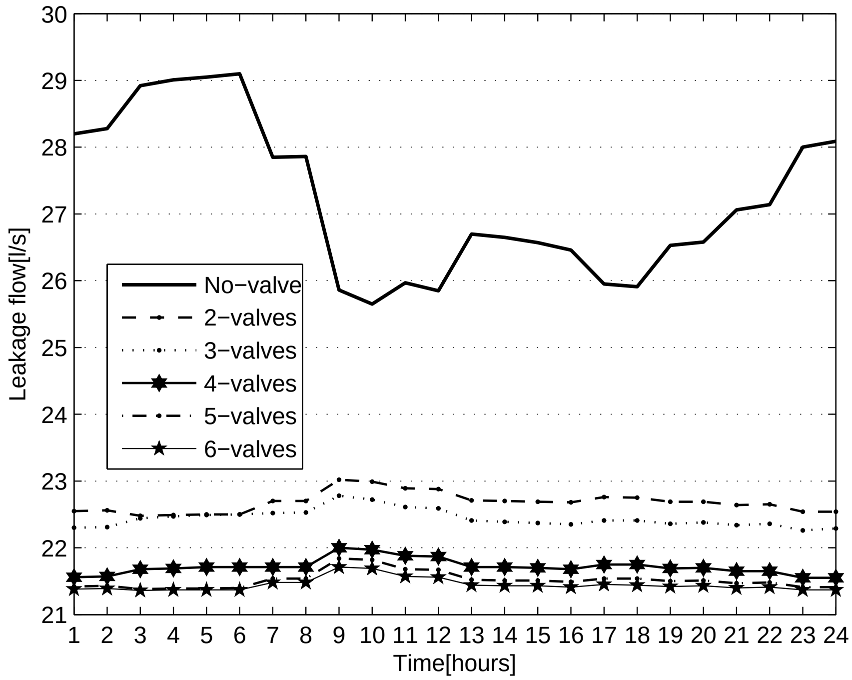


Figure 4.2: Dynamic leak flows

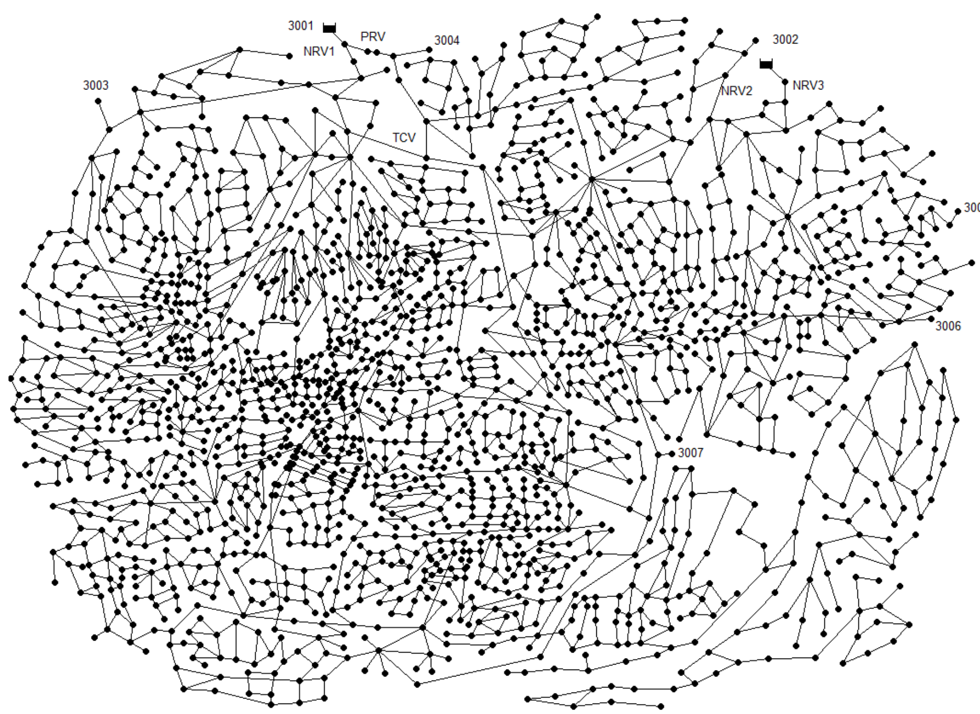


Figure 4.3: EXNET water distribution system[5]

Table 4.10: Penalty parameter values in different cases for solving the large-scale problem

No. of PRVs	Penalty parameter values	Number of iterations
3	4732.73	9
4	4976.60	63
5	2694.05	15
6	3899.49	28
7	4936.84	10
8	4993.80	62
9	4110.41	121
10	4265.89	107

4.5.2 Case study 2: Optimal PRV localization for a large-scale WDS

To evaluate the applicability of our approach to a large-scale WDS, the EXNET water distribution system [5] comprising 2463 links, 1890 nodes, and 2 reservoirs as shown in Figure 4.3 is studied. It should be noted that there exist a PRV and a TCV in the system. To study the PRV localization problem, we remove these two valves and replace them with the pipes with the same diameters. The minimal pressure required at all nodes is set to 8.0(m) as used by Eck and Mevissen in [35]. The resulting MINLP problem for one demand pattern has 6816 continuous variables, 4926 binary variables, and 6762 constraints. Using our approach, the optimal locations of PRVs are found for 3 to 10 PRVs. These optimal locations of PRVs and their pressure settings are passed to EPANET 2 [106] which calculates the excessive pressure as listed in Table 4.11. In the case of 3 PRVs, our approach obtains the links of 2699, 5162, and 3244, while the MINLP approach by Eck and Mevissen in [35] found optimal locations on the links of 2699, 4154, and 3046. The PRV locations found by our approach result in an excessive pressure of 48245.72(m), while it is 50293.55(m) with PRV locations by Eck and Mevissen [35]. Therefore, with the PRV locations from our approach a higher reduction of the excessive pressure (i.e. 2047.83 m) can be achieved. In addition, we solved the problem with more than 3 PRVs. As shown in Table 4.11, a higher number of PRVs leads to a higher reduction of the excessive pressure. The penalty parameter values, at which the solution is found by our approach and the number of iterations for solving the NLP problems are shown in Table 4.10. The computation time for solving the problems is shown in Table 4.11. In particular, in the case of 3 PRVs, it takes 1521.05(s) by our approach, while it took 456000.0(s) reported by Eck and Mevissen in [35].

Table 4.11: Optimal PRV locations for the EXNET network

	Reformulation approach			Eck and Mevissen [35]		
No. of PRVs	LinkIDs	CPU time [s]	Excessive-pressure [m]	LinkIDs	CPU time [s]	Excessive-pressure [m]
3	5162; 3244; 2699	1521.05	48245.72	4154; 3046; 2699	456000.0	50293.55
4	2938; 3244; 2699; 5120	7948.22	47465.01			
5	5162; 3046; 2699; 5120; 3244	1841.35	46768.24			
6	2938; 3046; 5162; 3244; 3593; 2699	3262.72	46354.12			
7	2700; 3783; 3046; 3244;5162; 5120;2699	1344.88	45594.31			
8	2700; 2938 ;4186; 3046; 5162; 5120; 3783; 2699	7620.85	45449.05			
9	2938; 3244; 2700; 3593; 3438; 5162; 5120; 3783; 2699	13164.56	44139.64			
10	2938; 3438; 3244; 3593; 2700; 5089; 5162; 5120; 3783; 2699	12910.89	43755.85			

4.6 Conclusions

In this chapter, we presented a reformulation approach for solving the MINLP problem for identifying optimal locations of PRVs in a WDS. The MINLP problem is reformulated as a MPCC which can be efficiently solved by NLP algorithms. The MPCC problem is regularized to a NLP using a penalization method which is solved by a sequence of NLP problems. A rounding scheme for the binary variables is proposed to accelerate the solution procedure and improve the quality of the MINLP solution. As a result, the solution will be found not only at the end of the MPCC (i.e., the limit point), but also during solving the sequence of NLPs. Using two case studies, the proposed approach was applied to the optimal PRV localization for a small and a large-scale WDS. The results revealed new locations of PRVs which result in higher reductions of leakage amounts and excessive pressures as compared with those given in the literature.

Chapter 5

Optimal Pressure Regulation in Water Distribution Systems Based on an Extended Model for Pressure Reducing Valves

In chapter 4, we have proposed a MPCC approach to identify optimal location of PRVs in a water distribution system to reduce the leakage flow. This chapter will present a nonlinear programming optimization approach to optimal pressure regulation in a WDS through controlling operations of pressure reducing valves (which have already been placed in a WDS).

Optimal pressure regulation to reduce water losses in water distribution systems (WDSs) becomes an important concern due to the increasing water demand and the threat of drought in many areas of the world. The leakage amount in a WDS depends heavily on its operating pressure and thus can be minimized by implementing optimal pressure strategies through pressure reducing valves (PRVs). To achieve this, a model-based optimization is necessary, where *an accurate model* of the PRVs is required. The PRV models having been used until now for pressure regulations are two-mode models which cannot circumstantiate many situations occurring in WDSs. In this chapter, we extend the existing model by a three-mode one for PRVs which is able to describe the required circumstances of pressure regulations in WDSs. The non-smoothness of this model is smoothed by an approximation approach, thus allowing the formulation and solution of a continuous nonlinear optimization problem for optimal pressure regulation. Two benchmark WDSs are used to verify our approach and it can be shown from the results that our PRV model outperforms the existing models in terms of the quality and accuracy of the optimal solutions.

5.1 Introduction

The increase of domestic and industrial demand leads to drastic water shortages in developing countries and the climate change causes growing water scarcities in drought areas. As a result, the reduction of water losses in water distribution systems (WDSs) has become a high priority for water utilities and regulators [23, 24].Water utilities have made major investments in many areas of water management such as detection and repairing of leakage, pipe rehabilitation programs, and optimal pressure control to decrease leakage [30].

Water leakages can be considered as additional demands at nodes and mathematically modeled as proportional relation to the nodal pressure [47]. The leakage amount in a WDS increases significantly when operating at an excessive pressure [48]. For this reason, reducing the excessive pressure will lead to a reduction of the leakage amount and the risk of further leaks in a WDS [30, 47, 48]. This can be accomplished by a model-based optimization aiming at optimal regulations (or schedules) of the pressure reducing valves (PRVs) and/or the isolated valves in WDSs [7, 37, 42].

Optimal pressure management can be casted as a nonlinear optimization problem [37, 42]. Many solution approaches have been proposed to address the optimization problem such as heuristic algorithms [34, 60] and nonlinear programming methods [37, 42]. In this work, our aim is to develop a fast and efficient algorithm to solve the optimization problem, so that a nonlinear programming method is used. The accuracy of the model used to describe the WDS under consideration plays an essential role in a NLP solution. Till now the model for PRVs having been used for optimal pressure regulation using NLP method is a two-mode model. A variable denoting the valve setting, varying between zero (fully closed) and one (fully open) is usually introduced to represent the operation of a PRV. This model can only represent the *normal mode* when a PRV maintains the downstream pressure at the preset value and the *open mode* when the downstream pressure is lower than the pressure setting. However, it cannot account for the check valve mode for preventing reverse flows when upstream pressure is lower than the downstream pressure. The *check valve mode* is important for situations with varying water demand, i.e., the water consumption drop considerably in the night, which take place in most WDSs.

In this chapter, we propose a non-smooth model, which is an extension of the existing model, to describe the hydraulic behaviors of PRVs. This model is able to circumstantiate the three (open, normal, check valve) operational modes of a PRV. The non-smoothness of the model is smoothed by using an interior-point approximation approach, so that it can be employed for the formulation of a NLP problem for optimal pressure regulations of WDSs. Two benchmark WDSs are taken as case studies to demonstrate the advantages of using the extended PRV model. It can be shown from many scenarios of demand patterns that the optimal results by using our PRV model outperform those by using the previous models. In addition, a higher accuracy of the solution can be achieved with our PRV model in comparison to that by using the models from the literature.

The remainder of this chapter is organized as follows. In section 5.2, we at first analyze the shortcomings of the existing PRV models and then propose an extended model. The formulation of a general optimization problem for optimal pressure regulation in WDSs is presented in section 5.3. In section 5.4, we apply the proposed PRV model to optimize pressure regulations for two benchmark WDSs. Conclusions of the paper are provided in section 5.5.

5.2 Model of a pressure reducing valve

5.2.1 The existing models

A pressure reducing valve is commonly described by the following equation [37]

$$Q_{i,j} = R_{i,j} V_{i,j} sign\left(H_i - H_j\right) \left|H_i - H_j\right|^{0.54} \tag{5.1}$$

where

$$\begin{aligned} R_{i,j} &= \frac{278.54 C_{i,j} D_{i,j}^{2.63}}{L_{i,j}^{0.54}} \\ 0 \le V_{i,j} &\le 1.0 \end{aligned} \tag{5.2}$$

where $C_{i,j}$, $D_{i,j}$, $L_{i,j}$ are the Hazen-Williams coefficient, the diameter, and the length of pipes.

It can be seen that Eq.(5.1) is non-smooth and thus its gradient will be discontinuous. Therefore the optimization problem based on this model will also be non-smooth and cannot be solved directly by a NLP solver. For this reason, a smoothing strategy is needed. In addition, it is important to prevent the evaluation of the derivatives at the point of discontinuity, i.e., when the heads H_i and H_j at the two end nodes of the PRV are equal [37]

Another form of a PRV model is described as [42].

$$H_i - H_j = k_{i,j}\left(\nu_{i,j}\right) R_{i,j} Q_{i,j} \left|Q_{i,j}\right|^{0.852} \tag{5.3}$$

where $R_{i,j}$ is the resistance of PRV; $k_{i,j}\left(\nu_{i,j}\right)$ is a resistance factor of the head loss related to valve opening $\nu_{i,j}$. $k_{i,j}\left(\nu_{i,j}\right)$ can take a value from 1.0 to a very large positive number (i.e., infinity)[42].

To use Eq.(5.3) in formulation of the NLP problem, an approximation $Q_{i,j} \simeq \left(Q_{i,j}^2 + \beta^2\right)^{0.5}$ can be used where β is a small value to smooth Eq.(5.3), so that it becomes

$$H_i - H_j = k_{i,j}\left(\nu_{i,j}\right) R_{ij} Q_{i,j} \left(Q_{i,j}^2 + \beta^2\right)^{0.426} \tag{5.4}$$

It can be seen that Eq.(5.4) can be used only if PRV operates with condition $H_i \ge H_j$, i.e. in the normal or open modes. However, the diurnal demand pattern in a WDS can fluctuate arbitrarily (i.e., the water consumption decreases significantly at the night) and thus there may be the case where the PRVs are forced to shut off when $H_i < H_j$ (the check valve mode). Therefore, it is not suitable to use this model in the formulation of the optimization problem for optimal pressure regulation with varying demand patterns. From the numerical solution point of view, it can make the NLP solver failed to solve the problem or converged to bad local solutions in many demand scenarios.

5.2.2 An extended model

In general, a PRV in a WDS can operate in one of the following three modes [120]. First, it operates in a normal mode (mode 1), i.e., its resistance ($R_{i,j}$) is adjusted to maintain the preset pressure on its downstream side. Second, it operates as a fully opened valve (mode 2), when its downstream pressure cannot be maintained, i.e., the pressure on the upstream and downstream side is less than the pressure setting. Third, it acts as a check valve to prevent the water flow in a reverse direction (mode 3), i.e., when the pressure on the downstream side is higher than the one on the upstream side. Therefore, it is necessary to model a PRV which can describe all three modes. Considering a PRV on a pipe connecting node i with head H_i to node j with head H_j, we can use the following equation to describe its head loss when operating in mode 1 and 2 with flow $Q_{i,j}$ [94, 121]

$$H_i - H_j = R_{i,j} Q_{i,j}^2 \tag{5.5}$$

In the normal mode (mode 1), the resistance $R_{i,j}$ is adjusted to maintain the pressure at node to a preset pressure setting. Mathematically, depending on the pressure setting, $R_{i,j}$ can range from a small value when the PRV acts as a fully opened valve to a very large value when it acts as a fully closed valve. In particular, in the open mode (mode 2), the resistance can be expressed as [94]

$$R_{i,j} = \frac{8K_{i,j}}{\pi^2 g D^4} \tag{5.6}$$

where $K_{i,j}$ is the head-loss coefficient and it can be taken as 10.0 [122, 123]. This means that in the open mode $R_{i,j}$ is fixed. In the normal mode (mode 1), we have

$$R_{i,j} > \frac{8K_{i,j}}{\pi^2 g D^4} \tag{5.7}$$

To represent the operation of PRV in the normal mode, we introduce a variable coefficient $v_{i,j}$ with $0 < v_{i,j} \leq 1$ to account for the variable resistance, so that Eq. (5.5) becomes

$$H_i - H_j = \frac{1}{v_{i,j}} R_{i,j} Q_{i,j}^2 \tag{5.8}$$

where $Q_{i,j} \geq 0$, i.e., the flow through the valve should be kept in one direction. The boundaries of this coefficient correspond to the two limiting operation cases of the normal mode of a PRV, namely it is fully closed in the case of $v_{i,j} \to 0$ and is fully opened in the case of $v_{i,j} = 1$.

Similar to Eq. (5.4), Eq. (5.8) can only describe mode 1 and mode 2 of PRVs. In the check valve mode (mode 3), the PRV should be fully closed and thus the flow though it is zero, i.e. $Q_{i,j} = 0$. To consider the operation mode 3 where a PRV acts to prevent a reverse flow when $H_i < H_j$, we extend Eq. (5.8) in the following form

$$\max(0, H_i - H_j) = \frac{1}{v_{i,j}} R_{i,j} Q_{i,j}^2 \tag{5.9}$$

This PRV model is able to describe all three operation modes required in optimal pressure regulation. However, Eq. (5.9) is a non-smooth equation and hence cannot be directly used for the formulation of a NLP problem. In this study, we propose to use the interior-point smoothing approach proposed in [102] to approximate the left-hand side of Eq. (5.9) by the following function

$$\max(0, H_i - H_j) \simeq \frac{(H_i - H_j) + \sqrt{(H_i - H_j)^2 + \tau^2}}{2} \tag{5.10}$$

where τ is a small value and chosen as 0.001. In this way, the smooth model which is able to describe the three modes of a PRV is expressed as

$$(H_i - H_j) + \sqrt{(H_i - H_j)^2 + \tau^2} = \frac{2}{v_{i,j}} R_{i,j} Q_{i,j}^2 \tag{5.11}$$

In the next section, we will integrate the models in the forms of Eq.(5.4), Eq. (5.8), and Eq.(5.11) in the formulation of NLP problems for optimal pressure regulation in WDSs. Results from case studies in section 5.4 will show the differences of the three models in terms of accuracy and feasibility.

5.3 Problem formulation for optimal pressure regulation

The aim of our optimization is to find optimal pressure settings for PRVs so as to minimize the excessive pressure in a WDS. Therefore, the objective function is defined as the excessive pressure at all nodes in the WDS in the optimization time horizon [47]

$$\min F = \sum_{i=1}^{N_n} \sum_{k=1}^{T} \left(H_{i,k} - H_{i,k}^L \right) \tag{5.12}$$

where N_n is the total number of nodes, T=24 hours is the time horizon, and $k = 1, ..., 24$ is time interval. We consider a WDS with NP pipes, N_r reservoirs and N_{prv} pressure reducing valves. The equality constraints consist of the following equations.

The continuity equation at nodes i

$$\sum_{j,k} Q_{j,i,k} - d_{i,k} - l_{i,k} = 0; i = 1, ..., N_n \tag{5.13}$$

The energy equations for pipes connecting node i to node j

$$- H_{i,k} + H_{j,k} + \Delta H_{i,j,k} = 0; i, j = 1, ..., NP \tag{5.14}$$

where the head loss ($\Delta H_{i,j,k}$) through a pipe connecting node i to node j is computed either by the Hazen- Williams equation [94]

$$\Delta H_{i,j,k} = \frac{10.67 L_{i,j}}{D_{i,j}^{4.87}} \left(\frac{Q_{i,j,k}}{C_{i,j}} \right)^{1.852} \tag{5.15}$$

or by the Darcy-Weisbach equation [94]

$$\Delta H_{i,j,k} = \frac{8 L_{i,j} f}{g \pi^2 D_{i,j}^5} \left| Q_{i,j,k} \right| Q_{i,j,k} \tag{5.16}$$

The friction factor f in (5.16) is implicitly calculated using the Colebrook-White equation [94]

$$\frac{1}{\sqrt{f}} = -2 \log \left(\frac{(\varepsilon / D)}{3.7} + \frac{2.51}{\mathrm{Re} \sqrt{f}} \right) \tag{5.17}$$

where Re is the Reynolds number

$$\mathrm{Re} = \frac{VD}{\nu} \tag{5.18}$$

In Eq.(5.15) and Eq.(5.16) L, D and C are the length, diameter and Hazen-William coefficient of pipe, respectively; ε in Eq. (5.17) is the pipe roughness coefficient; V and ν are the velocity of flow through the pipe and the viscosity of water, respectively.

The difference between Eq. (5.15) and Eq. (5.16) lies in the fact that Eq. (5.15) is a simple and smooth model with a lower accuracy [96], while the accuracy of Eq. (5.16) is much higher but it is more complicated and non-smooth. To use Eq.(5.16) in the formulation of a NLP, we use the smooth form proposed by [8]

The leakage amount associated to node i is calculated by [1, 32] .

$$l_{i,k} = C_L L_{t,i} p_{i,k}^{\gamma} \tag{5.19}$$

where

$$L_{t,i} = 0.5 \sum_j L_{i,j} \tag{5.20}$$

In (5.19) C_L is the discharge coefficient of the orifice and γ is the pressure exponent [1].

The energy equations for PRVs located in the pipe from node i to node j (see Eq. (5.11))

$$(H_i - H_j) + \sqrt{(H_i - H_j)^2 + \tau^2} - \frac{2}{v_{i,j}} R_{i,j} Q_{i,j}^2 = 0 \tag{5.21}$$

where $R_{i,j}$ is calculated by Eq.(5.6)

The head of reservoir i is considered as a constant ($\overline{H}_i$), i.e.

$$H_{i,k} - \overline{H}_i = 0; ; i = 1, .., N_r \tag{5.22}$$

The inequality constraints consist of following operational restrictions.

Nodal head constraints

$$H^L \leq H_{j,k} \leq H^U; j = 1, ..., N_n \tag{5.23}$$

Pipe flow constraints

$$Q^L \leq Q_{i,j,k} \leq Q^U; i, j = 1, ..., NP \tag{5.24}$$

Valve flow constraints

$$0 \leq Q_{i,j,k} \leq Q^U; i, j = 1, ..., N_{prv} \tag{5.25}$$

Valve variable coefficient constraints

$$0 < v_{i,j,k} \leq 1; i, j = 1, ..., N_{prv} \tag{5.26}$$

The model equations (Eq. (5.13) - Eq. (5.20)) and related parameters can be extracted from a simulation model in the EPANET 2 environment [58] using the EPANET Programmers Toolkit [124], if available. We use the IPOPT solver [117] to solve the nonlinear optimization problem formulated above. The Jacobian of the constraints as well as the gradient of the objective function are calculated and supplied to IPOPT. The brief description of IPOPT is given in the appendix B.1. All the computation experiments in the following case studies are carried out on an Intel (R) Core (TM) i7-2600 CPU 3.4GHz 12GB RAM desktop.

5.4 Case studies

5.4.1 Case study 1

At first, we apply our PRV model for optimal PRV pressure settings in a water distribution system as depicted in Fig.5.1. This WDS has 41 links and 29 nodes and was used as a case study for the PRV localization in [1]. We use the Hazen-Williams equations for the head loss calculation. We consider 5 PRVs located in pipes 1,11,20,21, and 29 as suggested in [36]. The data for the demand pattern and reservoir heads for 24 hours, the leakage coefficient C_L and the leakage exponent parameter γ are from [1]. The

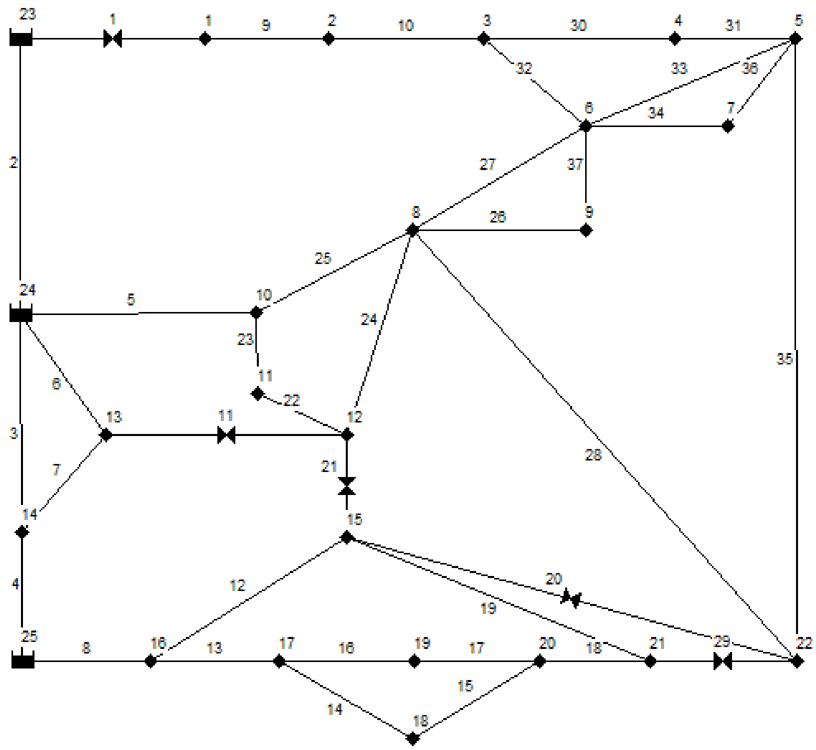


Figure 5.1: A water distribution system with 5 PRVs [6]

lower bounds for the pressure at the nodes are 30.0 (m). The optimal pressure regulation problem is formulated for 24 hours and the resulting NLP has 1608 equality and inequality constraints and 1800 variables. For comparison, we consider three demand patterns extended from the pattern given in [1] by different factors, as shown in Fig. 5.2.

IPOPT took an average of 4.53 s for solving the optimization problem. Corresponding to the demand pattern with factor equal to 1, the optimal pressure settings for PRVs on the link 1, 11, and 21 are given in Fig.5.3, while the PRV 20 and 29 are fully closed in the whole 24 hours. As a result, the average excessive pressure per hour and the average hourly leakage amount are given in Table 5.1. It can be seen that the average leakage amount and the average excessive pressure decrease 5.71(l/s) and 157.57(m), respectively, as compared with the case in which no pressure management (i.e., no PRV is installed in the WDS) is made.

To evaluate the accuracy of our proposed PRV model with the one in EPANET 2, we pass the optimal pressure settings for PRVs to EPANET 2 for comparison. It can be seen from Fig.5.4 that the leakage flows from the EPANET model are almost the same as those from our model. The absolute and relative discrepancies of flows and heads from the two models are shown in Fig. 5.6. The largest absolute discrepancy for the flows is less than 0.25(l/s) and it is about 0.022(m) for the heads. Therefore, it can be concluded that our PRV model is as accurate as the one used in EPANET 2.

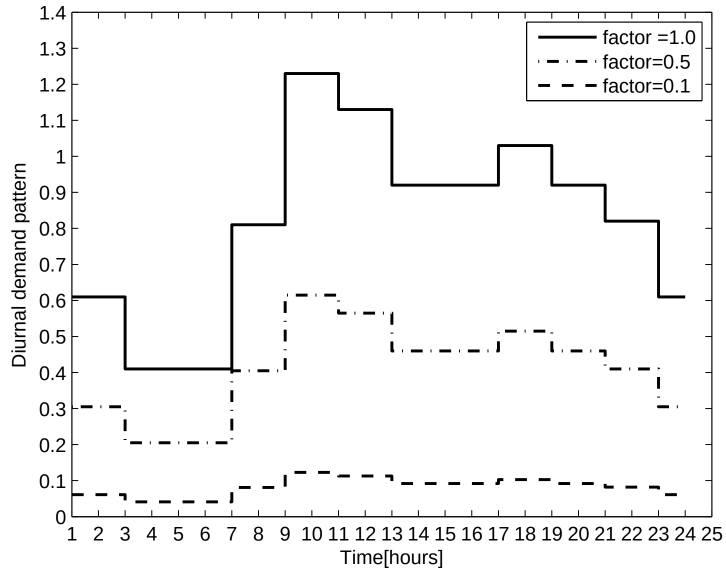


Figure 5.2: Demand profile for case study 1 [1]

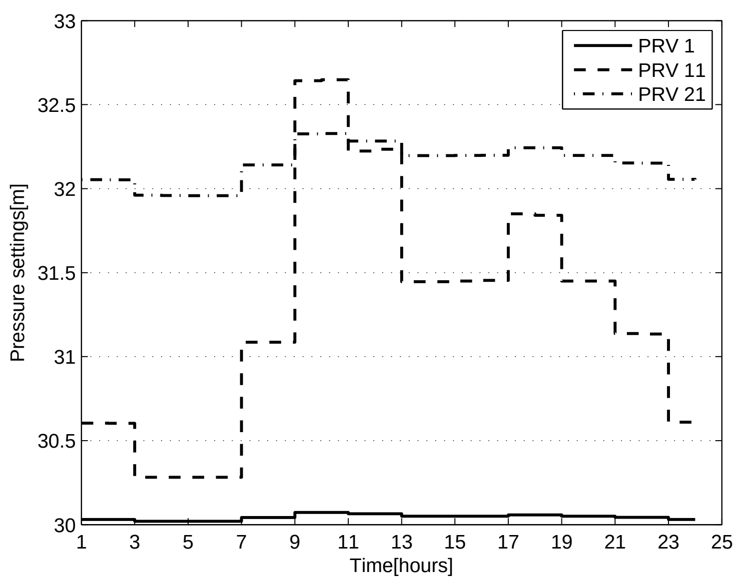


Figure 5.3: Optimal pressure settings

Table 5.1: Average leakage and excessive pressure in case study 1

	Without PRVs in WDS	With optimized regularization of PRVs
Average excessive pressure [m]	192.03	34.46
Average leakage flow[l/s]	27.14	21.42

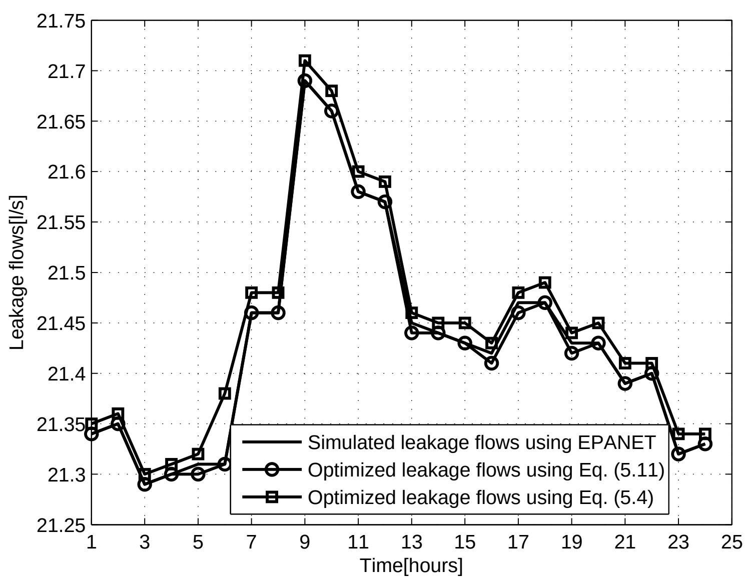


Figure 5.4: Simulated and optimized leak flows

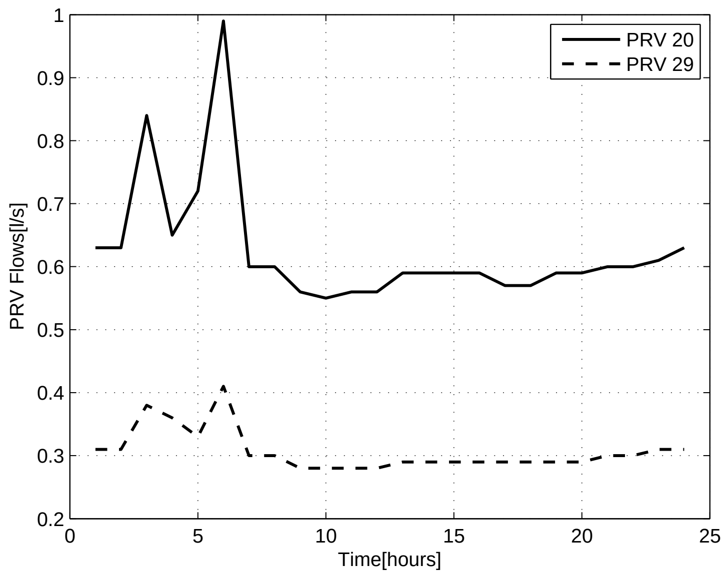
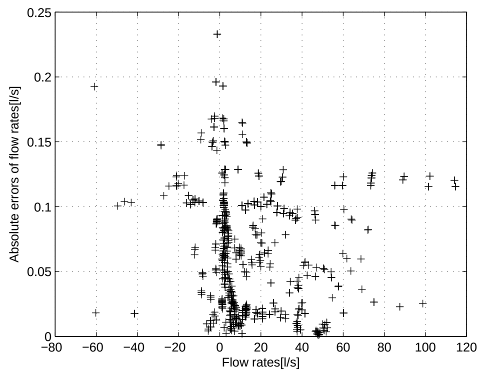


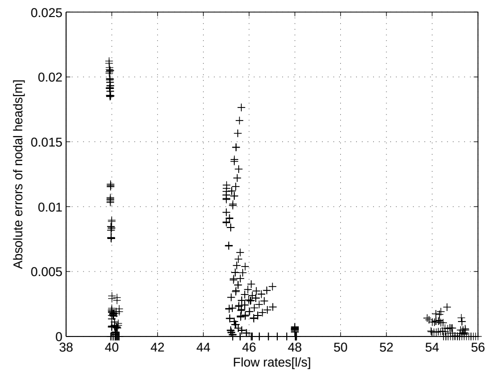
Figure 5.5: Flows through PRV 20 and 29 using the existing PRV model

To compare our PRV model with the existing model in the form of Eq.(5.4), we formulate the same optimization problem but with Eq.(5.4) as the PRV model in which $k_{i,j}$ ($\nu_{i,j}$) is bounded by 1.0 and 1.E+20 [42]. Then, we solve both optimization problems by IPOPT. It can be seen in Fig.5.4 that the existing model results in a bit higher leakage flows than those resulted from our model. This is because that the optimal flows through valves 29 and 20 should be zero (i.e., they are closed) with our PRV model, while they are nonzero (i.e., they operate in mode 1) with the existing PRV model as seen in Fig.5.5. In addition, as we pass the optimal PRV settings from the existing model to EPANET for simulation, EPANET 2 gives warnings that the system is unbalanced, while the solution from our PRV model is feasible for EPANET 2.

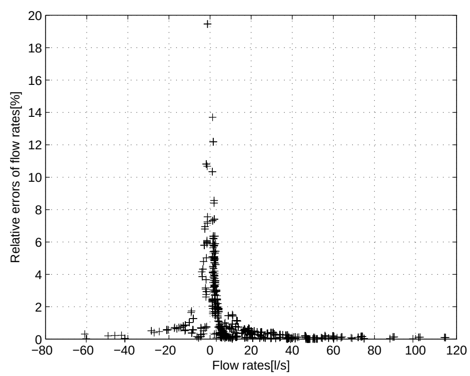
To illustrate the capability of our PRV model in handling varying demand scenarios, we change the current diurnal demand pattern by multiplying it with two factors 0.5 and 0.1 (as seen in Fig. 5.2). The results of the objective function and computation time for solving the problems based on Eq.(5.11) and Eq.(5.4) are given in Table 5.2. It can be seen that for both demand patterns our PRV model results in a lower objective function value (i.e., lower excessive pressure) than that by the existing PRV model. This is because the optimization problem based on Eq.(5.4) has a smaller feasible region, i.e., only when $k_{i,j}$ has a very large value (except for the case $H_i = H_j$) there will be a feasible solution for a PRV with $Q_{i,j} = 0$. On the contrary, using Eq.(11), a feasible solution for a PRV can be $Q_{i,j} = 0$ without requiring a very small value of $v_{i,j}$ (except the case $H_i = H_j$). The leak flows found by solving optimization problems corresponding to demand factors of 0.5 and 0.1 are shown in Fig.5.7. Again, it can be seen for both cases that our PRV model leads to higher decreases of leakage flows.



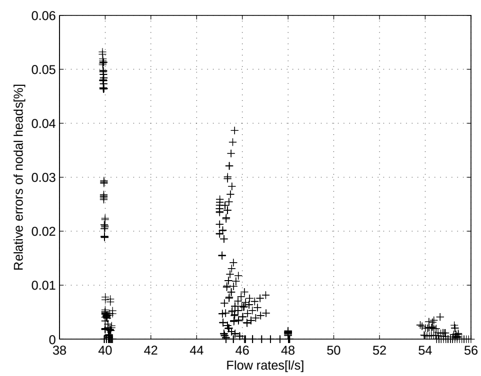
(a) Absolute errors of flows



(b) Absolute errors of heads



(c) Relative errors of flows

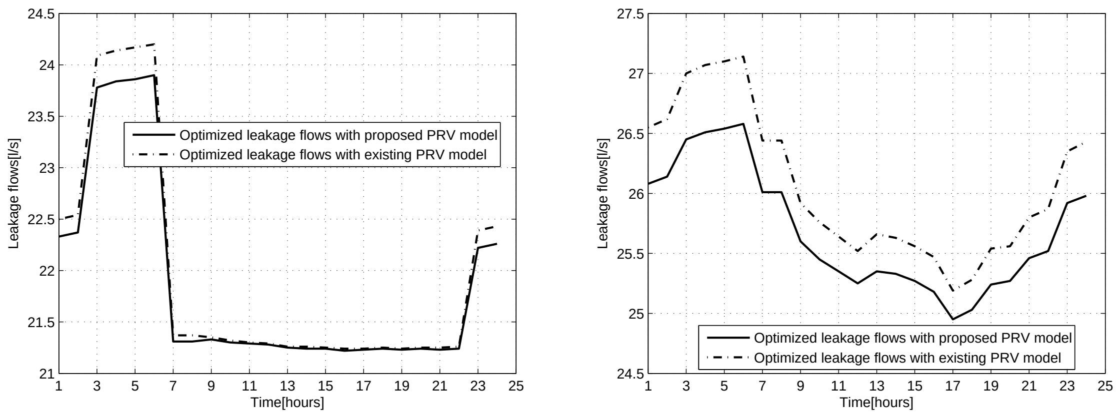


(d) Relative errors of heads

Figure 5.6: Relative and absolute discrepancies of flows and heads for case study 1

Table 5.2: Comparisons of solutions from two NLP problems

Multiplied factor for 24 demand patterns	Objective function value of NLP with Eq.(5.11)	Computation time(s)	Objective function value of NLP with Eq.(5.4)	Computation time (s)
0.1	5822.821	4.478	6079.166	0.736
0.5	2951.945	4.932	3026.338	0.738



(a) demand factor =0.5

(b) demand factor =0.1

Figure 5.7: Leak flows for two demand factors

5.4.2 Case study 2

Now we apply our PRV model to minimize the excessive pressure in the EXNET network as depicted in Fig.5.8 [2]. EXNET is one of the largest benchmark WDSs in the literature with 1892 nodes and 2465 links.To carry out optimal pressure regulation for this network, several modifications of the original model from [2] are necessary. We replace the existing TCV and the PRV in the network by a pipe with the same diameter and with the length of 10 (m) and the roughness of 1.5(mm) as well as 0.1(mm), respectively. The heads of reservoirs at nodes 3001 and 3002 are set to 80.0 (m) to avoid negative nodal pressures [35].

To regulate the excessive pressures, we consider 8 PRVs placed on link 5162 from node 155 to 1191, link 2699 from node 1390 to 1409, link 3046 from node 402 to 443, link 5120 from node 665 to 552, link 3783 from node 879 to 893, link 2700 from node 1397 to 1380, link 4186 from node 1081 to 1026, and link 2938 from node 643 to 590, as suggested in [36], as shown in Fig. 5.8.

In the EXNET network, at nodes 3003, 3004, 3005, 3006, and 3007 water is supplied from adjacent systems with the average flow rate values of 63.00, 1388.0, 10.77970, 926.0001, and 26.1027 (l/s), respectively [2]. We assume that the demand at these nodes is kept constant with these values for 24 hours. For all other nodes, we use the same basic demand data given in [2] with the demand pattern factors for 24 hours which are listed in Table 5.3. The lower bounds for pressures at all demand nodes are set to be 8.0 (m) [35].

Since the pipe hydraulics in EXNET is modelled by the non-smooth Darcy-Weisbach equation, we use the method by [8] to smooth the model, thus allowing formulating a continuous optimization problem. The resulting NLP has totally 104520 inequality and equality constraints and 104760 variables, respectively. It took only 237.195 s to solve this huge NLP problem. The optimal pressure settings (p_j) for the 8 PRVs are shown

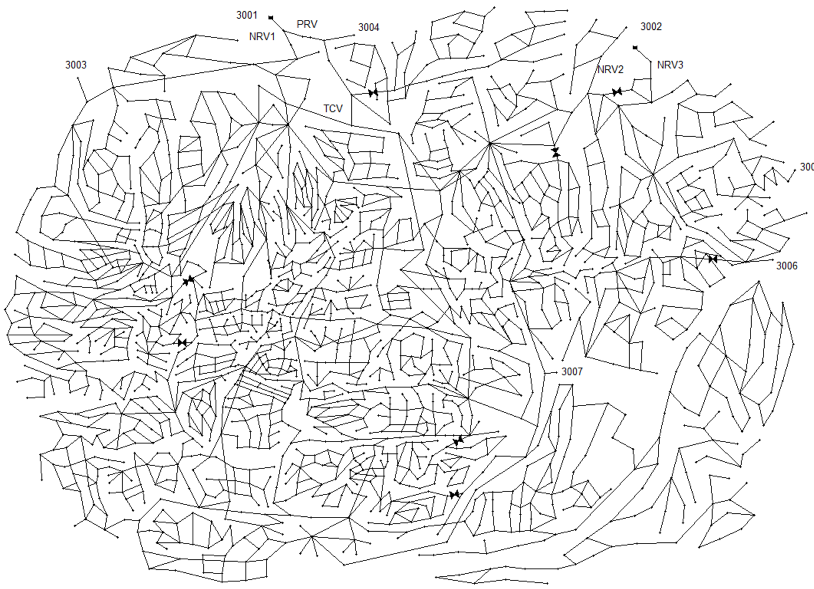


Figure 5.8: EXNET water distribution system[5]

Table 5.3: Daily water use pattern [2]

Time	1	2	3	4	5	6	7	8	9	10	11	12
	0.251	0.175	0.147	0.143	0.148	0.199	0.444	0.731	0.763	0.656	0.627	0.613
Time	13	14	15	16	17	18	19	20	21	22	23	24
	0.586	0.538	0.536	0.541	0.595	0.690	0.830	0.933	1.00	0.971	0.735	0.456

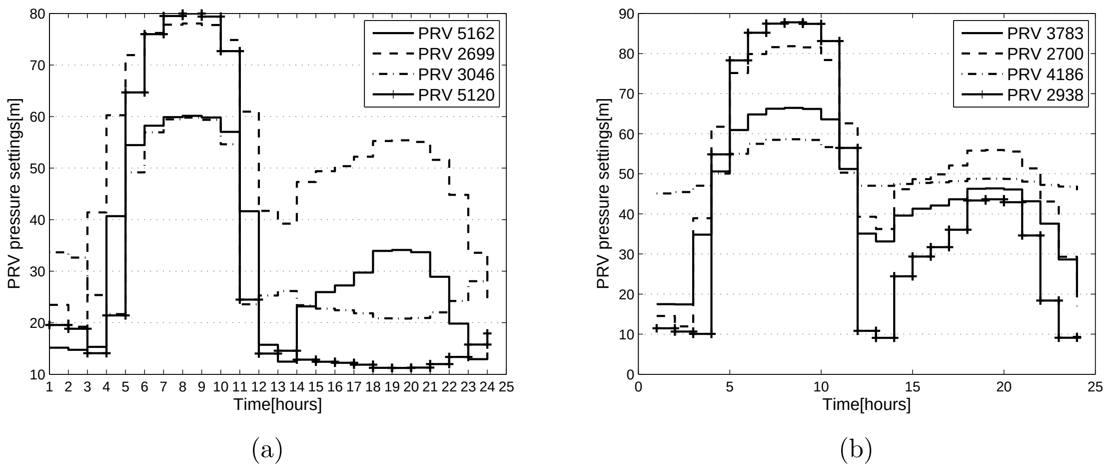


Figure 5.9: PRV pressure settings

in Fig. 5.9.

The average excessive pressures for 24 hours both with (dotted line) and without optimal pressure regulation (solid line) are computed using EPANET which are shown in Fig. 5.10. The solid line is generated by the simulation of the network with the same demand patterns, but without considering PRVs. It can be seen that with the optimal pressure regulation by controlling PRV operations, a significant reduction of the average excessive pressure is achieved. This pressure reduction will consequently lead to a significant decrease of the flow rates of the existing leakages and limit potential leaks which may occur in the network.

It can be also seen from Fig. 5.9 that the average excessive pressure will decrease when the demand increases (e.g., at time 21:00, demand factor =1.0). This is because, when more water is taken out at the nodes, the nodal pressures will be reduced and thus the excessive pressures $(H_i - H^L)$ decreased. Reversely, when the demand is small during the night, the excessive pressure will be high and thus the leakage amount will be increased. In addition, the pressure settings for the PRVs with a lower demand pattern factor tend to be higher than those with a higher demand pattern factor (see Table 5.3, Fig. 5.9 and Fig. 5.10).

The optimal flows through the PRVs by the proposed (solid line) and the EPANET (dotted line) model are given in Fig. 5.11 and 5.12. It can be seen that the discrepancies of the flows are quite small. In particular, the flows through the PRVs over the links 5162, 2699, 3046, 5120, 3783, and 2938 by our model are almost the same as the ones by EPANET 2. The discrepancies in flows of the PRVs over link 2700 and 4186 in several time intervals, caused by the smoothing method, do not affect much to the overall operation of the network since their values are very small (i.e., 1.8 and 0.37 l/s). Moreover, through a comparison of pipe flows and nodal heads resulted from our optimization model and those from EPANET 2, the largest absolute discrepancy of nodal heads is smaller than 0.75 (m), and the largest relative discrepancy is 5.7% and

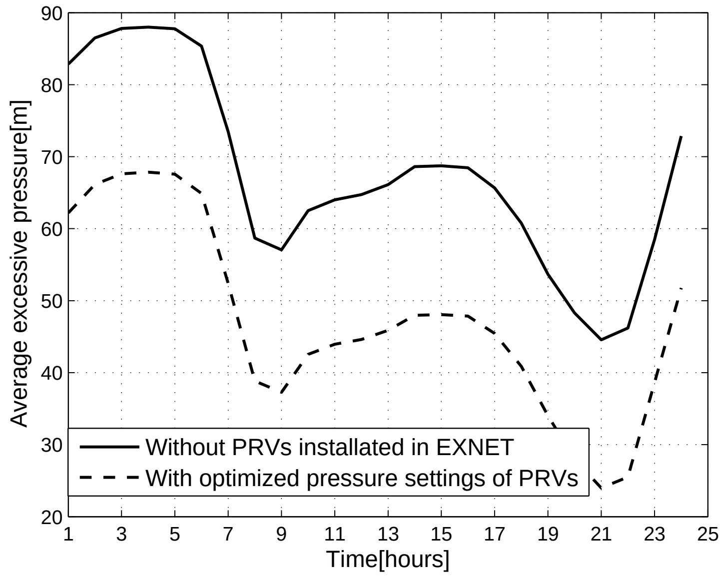
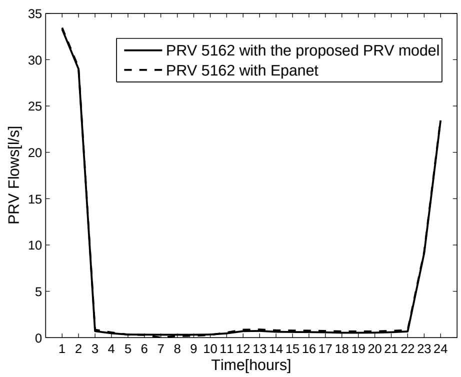


Figure 5.10: Average excessive pressure reduction

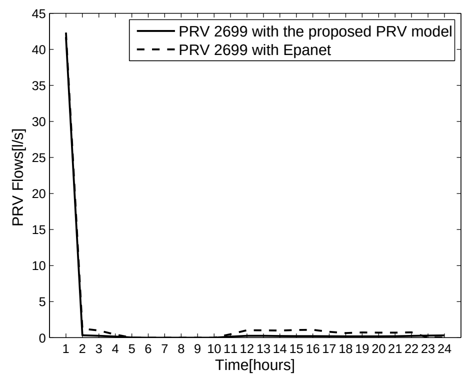
most of them is less than 2%. Similarly, for flows larger than 10 (l/s), the largest relative discrepancy is 5% and the most of them is less than 2.5%. Therefore, it can be concluded that the hydraulic model used in our optimization is sufficiently accurate

To demonstrate the advantage of our PRV model over the existing one, we also formulate an optimization problem based on Eq. (5.8). However, the NLP solver fails to solve the optimization problem in which 24 hours are considered. It can only solve the single optimization problem for several individual demand factors such as 1.0, 0.971, 0.933, and 0.830. For demand factors smaller than 0.830, it fails, since the condition $H_i - H_j \geq 0$ for the PRVs using Eq. (5.8) cannot be satisfied, i.e., the model cannot describe operation mode 3 (the check valve mode).

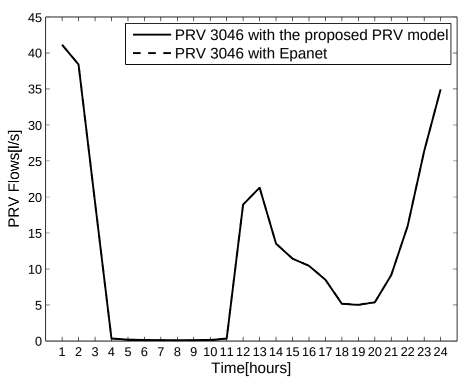
To see the operation of the PRVs using our model, we now take the PRV over the link 4186 as an example. As shown in Fig. 5.13, the head (H_i) at the upstream node is lower than that at the downstream node (H_j) from 3:00 to 11:00 and from 13:00 to 22:00. It means that during these time periods, this PRV operates in mode 3 that cannot be handled by Eq. (5.8).



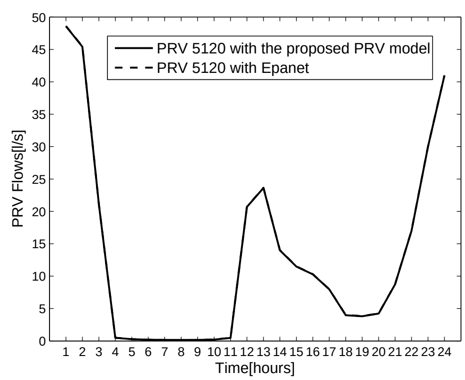
(a) Flows of PRV 5162



(b) Flows of PRV 2699

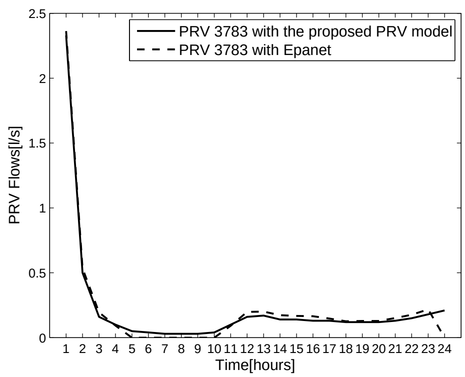


(c) Flows of PRV 3046

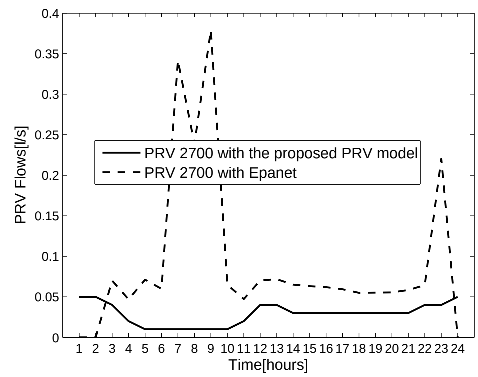


(d) Flows of PRV 5120

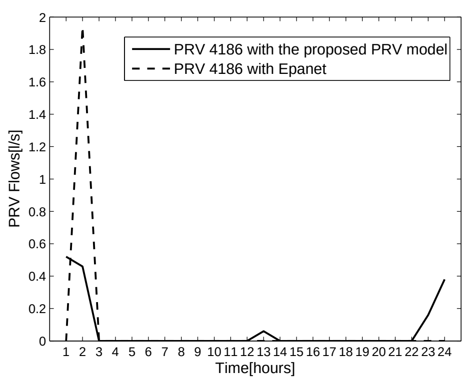
Figure 5.11: Comparisons of PRV flows



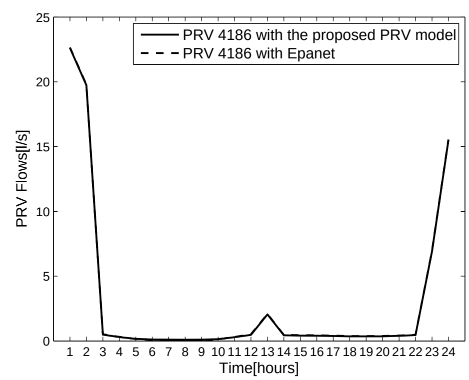
(a) Flows of PRV 3783



(b) Flows of PRV 2700



(c) Flows of PRV 4186



(d) Flows of PRV 2938

Figure 5.12: Comparisons of PRV flows

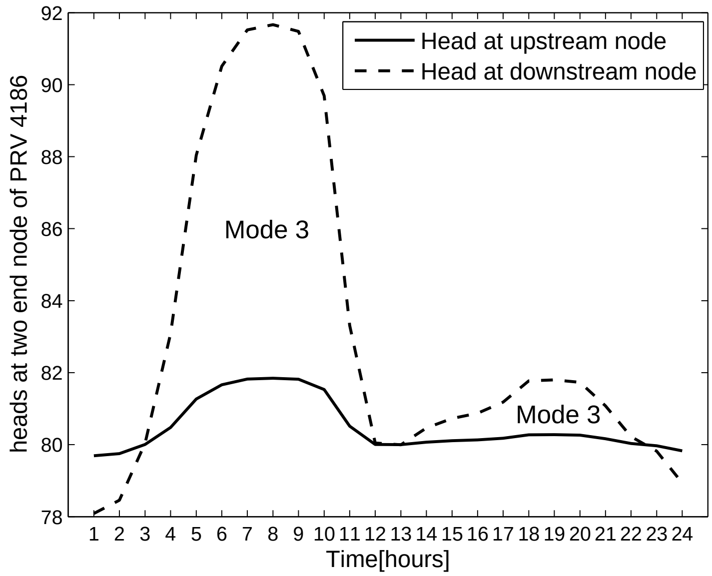


Figure 5.13: Heads at upstream and downstream nodes of PRV 4186

5.5 Conclusions

The task for the minimization of water leakage in WDSs poses a significant challenge. In this chapter, we present a systematic approach for optimal pressure regulation in WDSs by optimizing control of PRVs. An extended model for properly describing the three-mode behaviors of PRVs is proposed. This non-smooth model is then smoothed by using an interior-point approximation method, so that a continuous optimization problem is formulated and solved by a NLP solver. Based on the proposed PRV model, the minimization of the excessive pressures is carried out for two benchmark WDSs and the optimal results are compared with those obtained by using the existing PRV models. It can be shown that our PRV model is more beneficial and robust than the existing ones in terms of both quality and accuracy of the optimal solutions for many demand scenarios.

Chapter 6

Optimization of Energy and Maintenance Costs in Water Supply Systems

In this chapter, we develop a general mixed-integer nonlinear programming (MINLP) approach for optimizing the on/off operations of pumps in water supply systems with multiple reservoirs. The objective is to minimize the pumping energy cost and, at the same time, the pump maintenance cost should be kept at certain levels, which is achieved by constraining the number of pump switches. Due to the fact that pump switching is represented by a non-smooth function it is impossible to solve the resulting optimization problem by gradient based optimization methods. In this chapter, we propose to replace the switching function with linear inequality constraints in the formulation of MINLP. The reformulated constraints not only restrict pump switching, but also tighten the formulation by eliminating inefficient MINLP solutions. Two case studies with many different scenarios on the user-specified number of pump switches are taken to evaluate the performance of the proposed approach. It is shown that the optimized pump scheduling leads to the specified number of pump switches with reduced pumping energy costs.

6.1 Introduction

Water supply systems consume a significant amount of electrical energy to delivery water through the systems to customers and services. The largest cost in a water supply system is associated with the pump operation. Therefore, an optimal pumping schedule can reduce the energy cost significantly while fulfilling hydraulic and operational constraints. The basic idea of optimal pump scheduling for water utilities is to utilize the advantages of low priced tariff periods and shift the energy load in high priced tariff periods [3, 12, 61]. It can be shown that the application of an appropriate optimal pump scheduling can save 10% of the annual expenditure on energy and related costs [3].

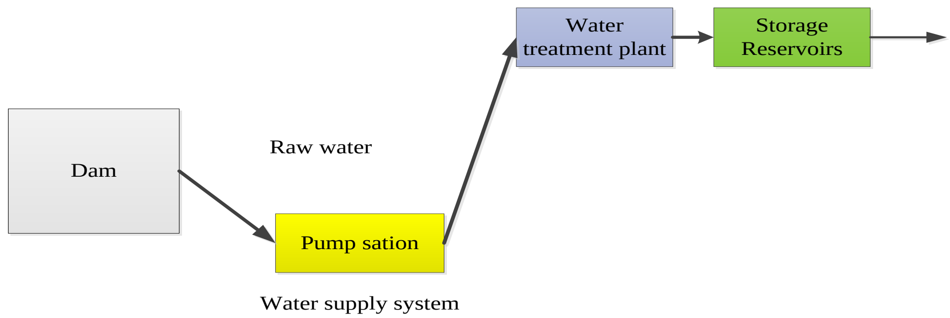


Figure 6.1: A water supply system with multiple reservoirs [3]

To utilize the advantage of low priced energy tariff, a time horizon for 24 hours should be considered for optimal pump scheduling [12]. McCormick and Powell in [125] used a two-stage optimization to minimize the pumping energy and maintenance costs. In the first stage, the optimal pump scheduling is found by solving a MILP problem, and it is further improved towards reduction of the energy cost and number of pump switches in the second stage by using Simulated Annealing (SA). The Dynamic programming (DP), Scatter search, and Tabu search were also applied to optimize pump scheduling problems [3, 126].

Operating with excessive pump switches will cause wear and tear of the pumps. This will increase the maintenance and repair costs [15, 125]. Thus an optimal pumping schedule should consider the pumping energy cost and the number of pump switches [15]. For this reason, a constraint to restrict pump switching is necessary. However, such a constraint is described by a non-smooth function [15], it cannot be used in the formulation of MINLP or MILP [125]. In [125, 127], a penalty function on pump switching is added to the objective function to address this issue.

We consider the water supply system as shown in Fig. 6.1 in which the raw water is pumped into the treatment plant where it is treated by chemical and physical processes. The pure water is stored in multiple reservoirs that serve as water buffers to satisfy the community's water demand by gravity [3, 19]. The purpose of chapter is twofold. First, we develop a general MINLP model for optimization of pump scheduling problems in water supply systems with multiple reservoirs. Second, we propose to use linear inequality constraints instead of the non-smooth pump switching constraint in formulation of MINLP. The idea of this kind of formulation comes from solving mixed-integer optimal control problems [128]. To the best of our knowledge, this method has not been applied to the restriction on pump switching in formulating optimal pump scheduling problems. The resulting MINLP has a nonlinear objective function and linear inequality constraints and hence it can be efficiently solved by available MINLP solvers. The difference between our proposed approach on handling pump switches and the ones in [125] lies in the fact that the maximum number of pump switches is clearly defined, while it is not the case when a penalty function is used as in [125]. Two case studies with

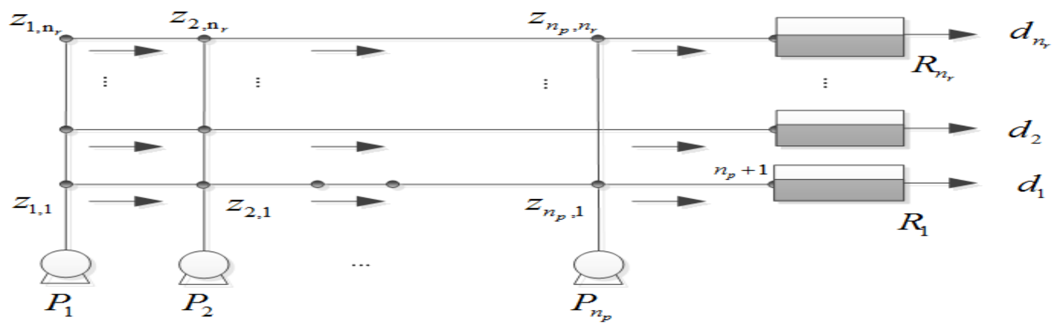


Figure 6.2: Pumping system in the water supply system

different scenarios on specified number of pump switches with multiple reservoirs are taken to evaluate the proposed approach. Based on the optimal results, the operators can select the pump scheduling with both the pumping energy cost and the desirable number of pump switches.

The remainder of this chapter is organized as follows. Section 6.2 presents the MINLP model for optimization of pump scheduling for water supply systems. Section 6.3 presents two case studies for determining optimal pump scheduling. Handling the number of pump switches by restricting the on/off time periods for pump is given in section 6.4. Conclusions of the paper are provided in section 6.5.

6.2 Problem definition and solution approach

We consider a water supply system with n_p pumps and n_r reservoirs depicted in Fig.6.2. The water demand pattern and electrical tariff are given. The MINLP is formulated in a time horizon T=24 (hours).

6.2.1 Pumping energy cost

For simplification, we at first formulate the MINLP for the system with one reservoir (i.e., R_1). The formulation of MINLP for the system with multiple reservoirs is then extended.

The electrical power consumption of pump i is calculated by [19]

$$P_i = \frac{\rho g z_i Q_i H_i}{\eta_i} \tag{6.1}$$

where Q_i is the flow of pump i (m^3/s); H_i is the total dynamic pump head (m); g is the acceleration to gravity (m/s^2); η_i is the efficiency of pump i; $z_i \in \{0, 1\}$ is a binary variable representing on/off operation of the pump.

For a system with n_p pumps, the pumping energy cost in the time horizon T will be

$$E{=}\sum_{k=1}^{T}\sum_{i=1}^{n_p} P_{i,k}\gamma_k \Delta t_k \tag{6.2}$$

where γ_k is electrical tariff at time interval k; Δt_k=1 (hour) is length of time interval k (k =1,...,T).
In equation (6.1), the total dynamic head of pump i is calculated by [3]

$$H_i = H_{st} + H_r\left(Q\right) + \Delta H_f\left(Q\right) + \Delta H_m\left(Q\right) \tag{6.3}$$

where H_{st} is static head and it is equal to the difference between elevation of reservoir and pump discharge; $H_r(Q)$ is the water level in reservoir. It depends on the amount of pumping water, water demand, and initial water level in the reservoir; $\Delta H_m\left(Q\right)$ is local head loss of pump i; $\Delta H_f\left(Q\right)$ is the head loss across pipe sections from pumps to reservoirs (i.e., pipe sections from pump p_i to reservoir R_1 at index n_p+1 as shown in Fig.6.2). The sum of local and pipe section head losses can be approximated by [19]

$$\Delta H_f + \Delta H_m \simeq 1.1\Delta H_{li} \tag{6.4}$$

with

$$\Delta H_{li} = \Delta H_{p_i,i} + \sum_{j=i}^{n_p} \Delta H_j \tag{6.5}$$

where $\Delta H_{p_i,i}$ is the head loss in the pipe section (p_i,i); ΔH_j is the head loss in the pipe section $(j;j+1)$, with $j=1,...,n_p$, $i=1,...,n_p$.

$$\Delta H_{p_i,i} = \frac{8\lambda_i L_i {(z_i Q_i)}^2}{g\pi D_i^5} \tag{6.6}$$

where L_i is the length of pipe section (p_i,i); D_i is the diameter of the pipe; Here we use the approximated value of friction factor $\lambda_i \approx 0.109$ [19]. In addition, head loss on pipe section $(j;j+1)$ is calculated by

$$\Delta H_j = \frac{8\lambda_j^{'} L_j \left(\sum\limits_{m=1}^{j} z_m Q_m\right)^2}{g\pi D_j^5} \tag{6.7}$$

with $\lambda_j^{'} \approx 0.093$ [19] and $\sum\limits_{m=1}^{j} z_m Q_m$ is the flow in the pipe section $(j;j+1)$. From the above equations, we obtain the equation of total head loss on pipe sections from pump p_i to reservoir R_1 is

$$\Delta H_{li} = \left(\frac{8\lambda_i L_i Q_i^2}{g\pi^2 D_i^5}\right) z_i^2 + \sum_{j=i}^{n_p} \frac{8\lambda_j^{'} L_j \left(\sum\limits_{m=1}^{j} z_m Q_m\right)^2}{g\pi^2 D_j^5} \tag{6.8}$$

Replace equations (6.3), (6.8), and (6.1) into (6.2), the energy cost by pump i during time period Δt_k is

$$\begin{aligned} E_{i,k} &= \gamma_k \frac{\rho g \left(z_{i,k} Q_i\right) \left(H_{st} + H_{r,k}\left(z_{i,k}, Q\right) + 1.1 \Delta H_{li}\right)}{\eta_i} \Delta t_k \\ &= \gamma_k \Delta t_k \frac{\rho g \left(z_{i,k} Q_i\right)}{\eta_i} \left\{ H_{st} + H_{r,k}\left(z_{i,k}, Q\right) + 1.1 \left[\left(\frac{8 \lambda_i L_i Q_i^2}{g \pi^2 D_i^5}\right) z_{i,k}^2 + \sum_{j=i}^{n_p} \frac{8 \lambda_j' L_j \left(\sum_{m=1}^{j} z_{m,k} Q_m\right)^2}{g \pi^2 D_j^5} \right] \right\} \end{aligned} \tag{6.9}$$

6.2.2 Linear inequality constraints

In this work, the hydraulic mass balance model is used to represent the equilibrium principle between the amount of water coming to and out of the reservoirs (i.e., water demand $Q_{r,j}$) [15, 19, 125, 126]. The water levels ($H_{r,k}$) of reservoir r with cross-sectional area S_r is calculated by the following equation:

$$H_{r,k} = H_{r,1} + \sum_{j=1}^{k-1} \frac{\Delta t_j}{S_r} \left(\sum_{i=1}^{n_p} \left(z_{i,j} Q_i\right) - Q_{r,j} \right) \tag{6.10}$$

and it is bounded by the minimum and maximum allowable water levels (H_{min} and H_{max})

$$H_{\min} \leqslant H_{r,k} \leqslant H_{\max} \tag{6.11}$$

Moreover, the final water levels in reservoirs should be at least the initial ones. So that,

$$H_{r,1} \leqslant H_{r,T} \tag{6.12}$$

In order to reduce maintenance cost for pumps, a constraint on pump switching is to be introduced. In this study, we use the following constraint [45, 128]

$$\sum_{i=1}^{n_p} \sum_{k=1}^{T-1} \left| z_{i,k} - z_{i,k+1} \right| \leqslant N_{\max} \tag{6.13}$$

This constraint is non-smooth since it contains the absolute term. However, it can be handled by a set of linear inequalities defining facets of feasible MINLP solution [128]

$$\begin{aligned} &sw_{i,k} \geqslant z_{i,k} - z_{i,k+1} \\ &sw_{i,k} \geqslant -z_{i,k} + z_{i,k+1} \\ &\sum_{i=1}^{n_p} \sum_{k=1}^{T-1} sw_{i,k} \leqslant N_{max} \end{aligned} \tag{6.14}$$

where $sw_{i,k} = |z_{i,k} - z_{i,k+1}|$; N_{max} is maximum number of pump switches and it is predefined. From the equation of energy cost (6.9) and constraints (6.11),(6.12), and (6.14), we have the following MINLP problem for optimal pump scheduling:

$$\min\ E = \sum_{k=1}^{T} \Delta t_k \gamma_k \left\{ \sum_{i=1}^{n_p} \frac{\rho g Q_i}{\eta_i} z_{i,k} \left[\begin{array}{l} H_{st} + H_{r,k}(z_i, Q) \\ +1.1 \left(\left(\dfrac{8\lambda_i L_i Q_i^2}{g\pi^2 D_i^5} \right) z_{i,k}^2 + \displaystyle\sum_{j=i}^{n_p} \dfrac{8\lambda' L_k \left(\sum\limits_{m=1}^{j} z_{m,k} Q_m \right)^2}{g\pi^2 D_k^5} \right) \end{array} \right] \right\}$$

$$\begin{array}{l} s.t. \\ H_{r,k} = H_{r,1} + \displaystyle\sum_{j=1}^{k-1} \frac{\Delta t_j}{S_r} \left(\sum_{i=1}^{n_p} (z_{i,j} Q_i) - Q_{r,j} \right) \\ H_{r,1} \leqslant H_{r,T} \\ sw_{i,k} \geqslant z_{i,k} - z_{i,k+1} \\ sw_{i,k} \geqslant -z_{i,k} + z_{i,k+1} \\ \displaystyle\sum_{i=1}^{n_p} \sum_{k=1}^{T-1} sw_{i,k} \leqslant N_{max} \\ i = 1, ..., n_p;\ \ k = 1, ..., T-1;\ g = 1, .., k-1 \end{array} \tag{6.15}$$

To simplify the expression, we further represent the objective function in the following form

$$E = \sum_{k=1}^{T} \Delta t_k \gamma_k \left\{ \sum_{i=1}^{n_p} \left[a_{i,k}(z) z_{i,k} + c_i z_{i,k}^3 + b_i z_{i,k} \left(\sum_{j=i}^{n_p} \frac{L_j \left(\sum\limits_{m=1}^{j} z_{j,k} Q_j \right)}{D_j^5} \right) \right] \right\} \tag{6.16}$$

where $a_{i,k}$,b_i, and c_i are defined as:
$a_{i,k}(z) = a_i (H_{st} + H_{r,k}(z_i, Q))$, $a_i = \frac{\rho g Q_i}{\eta_i}$, $c_i = \frac{8.8\rho\lambda_i L_i Q_i^3}{\pi^2 \eta_i D_i^5}$, $b_i = \frac{8.8\rho\lambda_i' Q_i}{\pi^2 \eta_i}$. The term $a_{i,k}(z)$ can be further expressed as

$$\sum_{i=1}^{n_p} z_{i,k} a_{i,k} = \frac{\rho g Q_i}{\eta_i} \sum_{i=1}^{n_p} \left(z_{i,k} (H_{r,1} + H_{st}) + \sum_{g=1}^{k-1} \frac{\Delta t_g}{S_r} \left(\sum_{u=1}^{n_p} z_{iu,kg} Q_u - z_{i,k} Q_{r,g} \right) \right) \tag{6.17}$$

where $z_{iu,kg} = z_{i,k} z_{u,g}$, $i = 1, ..., n_p; u = 1, ..., n_p; g = 1, ..., k-1$. Because $z_{i,k}$ is binary variable, we have $z_{i,k} = z_{i,k}^2 = z_{i,k}^3$ [129]. In this way, the objective function in (6.16) is simplified and generalized to the expression bellows:

$$E=\sum_{k=1}^{T}\Delta t_k\gamma_k\left\{\begin{array}{l}\dfrac{\rho g Q_i}{\eta_i}\displaystyle\sum_{i=1}^{n_p}\left(z_{i,k}\left(H_{r,1}+H_{st}\right)+\sum_{g=1}^{k-1}\frac{\Delta t_g}{S_r}\left(\sum_{u=1}^{n_p}z_{iu,kg}Q_u-z_{i,k}Q_{r,g}\right)\right)\\ +\displaystyle\sum_{i=1}^{n_p}\left(c_i+b_iQ_i^2\sum_{j=i}^{n_p}LD_j\right)z_{i,k}\\ +\displaystyle\sum_{i=1,i<j<n_p}^{n_p-1}\left\{\begin{array}{l}b_i\left(\displaystyle\sum_{l=j}^{n_p}LD_l\right)\left(Q_j^2+2Q_iQ_j\right)+\\ b_j\left(\displaystyle\sum_{l=j}^{n_p}LD_l\right)\left(Q_i^2+2Q_iQ_j\right)\end{array}\right\}z_{ij,k}\\ +2\left(\displaystyle\sum_{i=1,i<j<h<n_p}^{n_p}\left(\sum_{l=h}^{n_p}\left(LD_l\right)\left(b_hQ_iQ_j+b_iQ_hQ_j+b_jQ_iQ_h\right)z_{ijh,k}\right)\right)\end{array}\right\}\tag{6.18}$$

In the expression, we define $z_{ij,k}=z_{i,k}z_{j,k}$, $z_{ijh,k}=z_{i,k}z_{j,k}z_{h,k}$, and $LD_j=L_j\big/D_j^5$

6.2.3 The formulation of MINLP for water supply system with multiple reservoirs

Now the objective function E in (6.18) is extended for a system with n_r reservoirs as follows:

$$E=\sum_{k=1}^{T}\Delta t_k\gamma_k\sum_{r=1}^{n_r}\left\{\begin{array}{l}\dfrac{\rho g Q_i}{\eta_i}\displaystyle\sum_{i=1}^{n_p}\left(z_{i,r,k}\left(H_{r,1}+H_{st,r}\right)+\sum_{g=1}^{k-1}\frac{\Delta t_g}{S_r}\left(\sum_{u=1}^{n_p}z_{iu,r,k,g}Q_u-z_{i,r,k}Q_{r,g}\right)\right)\\ +\displaystyle\sum_{i=1}^{n_p}\left(c_i+b_iQ_i^2\sum_{j=i}^{n_p}LD_j\right)z_{i,r,k}\\ +\displaystyle\sum_{i=1,i<j<n_p}^{n_p-1}\left\{\begin{array}{l}b_i\left(\displaystyle\sum_{l=j}^{n_p}LD_l\right)\left(Q_j^2+2Q_iQ_j\right)+\\ b_j\left(\displaystyle\sum_{l=j}^{n_p}LD_l\right)\left(Q_i^2+2Q_iQ_j\right)\end{array}\right\}z_{ij,r,k}\\ +2\left(\displaystyle\sum_{i=1,i<j<h<n_p}^{n_p}\left(\sum_{l=h}^{n_p}\left(LD_l\right)\left(b_hQ_iQ_j+b_iQ_hQ_j+b_jQ_iQ_h\right)z_{ijh,r,k}\right)\right)\end{array}\right\}\tag{6.19}$$

where $z_{i,r,k}$, a binary variable which is used to indicate whether pump i supplies water to reservoir r or not. In addition, following constraints are used to ensure that at a particular time interval (k) a switched on pump will only supply water to one of the reservoirs.

$$\sum_{r=1}^{n_r}z_{i,r,k}\leqslant 1,\quad i=1,...,n_p,k=1,..,T\tag{6.20}$$

Table 6.1: Data for case study 1

a_i	b_i	c_i	$Q_i(\mathrm{m}^3/s)$	$L_k(\mathrm{m})$	$D_k(\mathrm{m})$
86.33	0.005	4.8	0.04	938.6	0.25
59.2	0.005	1.89	0.035	1,936.3	0.35
65.18	0.005	4.331	0.04	1,352.6	0.4
55.42	0.005	4.069	0.035	1,191	0.45
70.89	0.005	1.414	0.05	3,684	0.5
64.94	0.005	2.456	0.05	864	0.6
68.09	0.005	0.074	0.05	2,381	0.6
81.61	0.005	5.276	0.07	331.1	0.7
32.07	0.0032	11.693	0.025	625	0.8
28.03	0.005	3.21	0.025	11,3	0.9

The linear inequality constraints on number of pump switches in (6.14) are extended as:

$$\begin{aligned} &sw_{i,r,k} \geqslant z_{i,r,k} - z_{i,r,k+1} \\ &sw_{i,r,k} \geqslant -z_{i,r,k} + z_{i,r,k+1} \\ &\sum_{r=1}^{n_r}\sum_{i=1}^{n_p}\sum_{k=1}^{T-1} sw_{i,r,k} \leqslant N_{max} \end{aligned} \tag{6.21}$$

To solve the optimization problem formulated above, we employ the MINLP solver BONMIN [130] in GAMS [119]. In BONMIN, several MINLP algorithms are integrated (See in the appendix C). All the computation experiments in the following case studies are conducted on an Intel (R) Core (TM) i7-2600 CPU 3.4GHz 12GB RAM desktop.

6.3 Case studies

6.3.1 Case study 1

We consider at first a water supply system comprising of ten pumps and one reservoir as shown in Fig.6.3. The data for formulating the optimization problem modified from [19] is given in Table 6.1 The MINLP problem formulated has 240 binary variables and 507 linear constraints. The base water demand (Q_r) for the reservoir is assumed to be 0.35(m^3/s). The demand patterns are assumed to be 0.8 for periods from 1.00 a.m. to 6.00 a.m., 1.0 for periods from 7.00 a.m. to 20.00 , and 0.8 for periods from 21.00 to 24.00. The energy priced tariff is assumed to be 0.024($/kW) for periods from 1.00a.m. to 6.00a.m., and 0.1194 ($/kW) for periods from 7.00 a.m. to 24.00. The initial water level in the reservoir ($H_{r,0}$) is 15(m). The lower and upper bounds for water levels in the reservoir are 7.0 (m) and 28.0(m), respectively. Static heads (H_{st}) for all pumps are assumed to be 35(m).

The energy costs with respect to the scenarios on the maximum number of pump

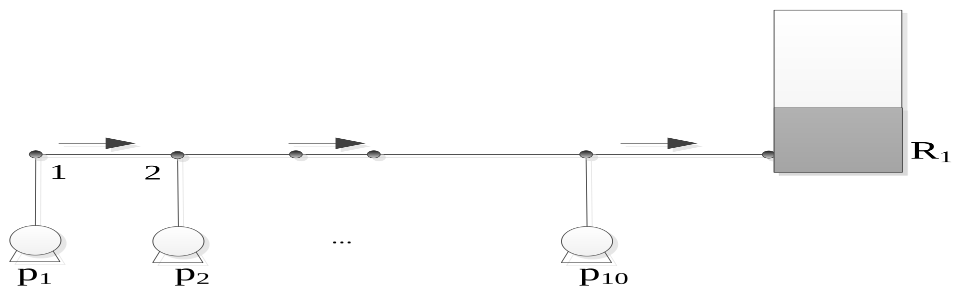


Figure 6.3: A water supply system in case study 1

Table 6.2: Objective function values with number of pump switches

Objective function values ($/day)	Computation time (s)	Maximum number of pump switches (N_{max})
869.77	0.196	1
825.85	115.924	2
812.25	109.699	3
799.28	172.319	4
787.91	97.298	5
768.73	62.666	6
757.88	1.529	7
757.88	2.901	8
757.88	14.352	–

-: without pump switching constraint

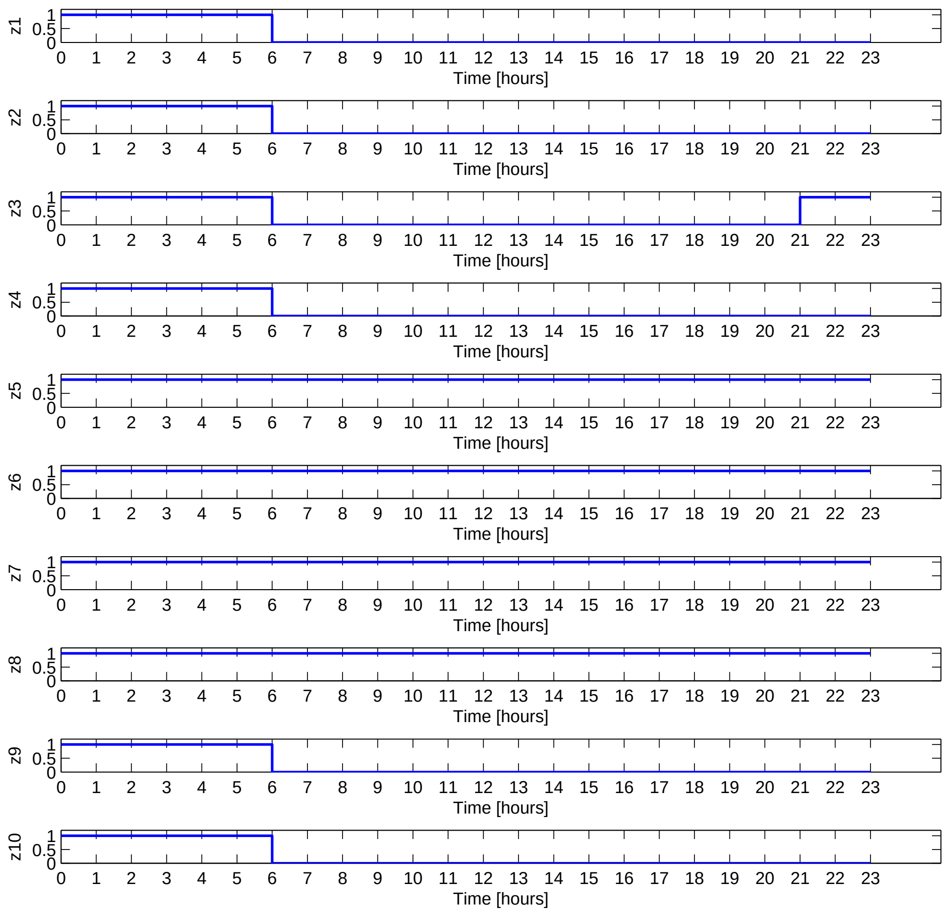


Figure 6.4: Optimal pumping schedules with N_{max}=7.

switches are given in Table 6.2. It can be seen that the pump scheduling with higher allowable number of pump switches will result in a lower pumping energy cost, and the same is true reversely. Interestingly, as the allowable number of pump switches is larger than 6, the optimized pumping schedules produce the same pumping energy costs (see in Table 6.2). The computation time for solving each of the MINLP problems is also shown in Table 6.2. It can be seen that while BONMIN takes 14.352 (s) to solve the optimization problem without using the pump switching constraint, it requires only 1.529 (s) for solving the one with the pump switching constraint (N_{max}=7). It means that the introduction of the constraint on the number of pump switches tightens the MINLP by eliminating inefficient MINLP solutions and therefore the computation time can be reduced.

The optimal solution (for the case N_{max}=7) shown in Fig.6.4 indicates that all pumps

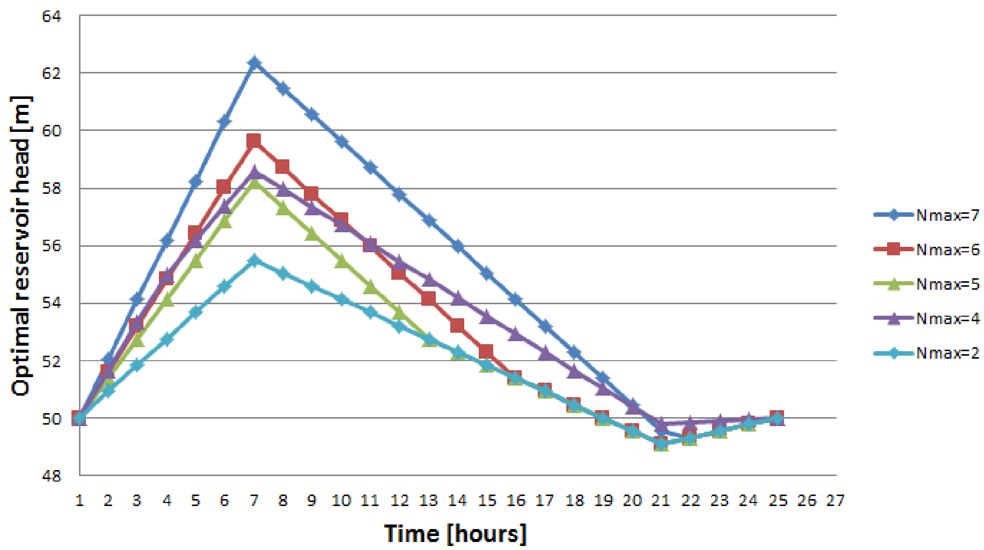


Figure 6.5: Reservoir head trajectories for different allowable number of pump switches.

are scheduled to operate in the low tariff periods (e.g., 1 to 6). In the high tariff periods, the optimized scheduling will use the pumps with higher efficiency (e.g., low value of a_i) which are near the reservoir to operate. In particular, during the high tariff periods pumps 5,6,7, and 8 are operated, while pump 1 and 2 are switched off (see Fig.6.4). The reason for the priority of selecting pumps near reservoir to be switched on is due to the fact that the total head losses on the sections of pipes will be much smaller than those located far from the reservoir. As shown in Fig.6.5, the optimized pump scheduling also allows the reservoir to be filled during the low tariff periods and emptied during the high tariff periods to supply water to the systems. Moreover, the reservoir recovers its initial water level by the end of scheduling period. It can be also seen in Fig. 6.6, as the maximum number of pump switches increases, the pumping energy cost decreases.

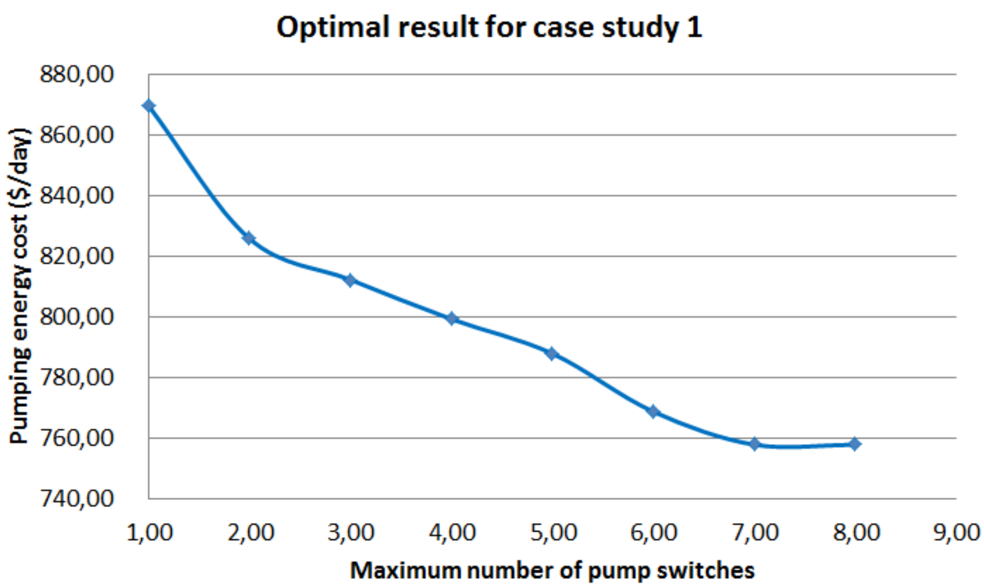


Figure 6.6: Objective function values with different allowable number of pump switches.

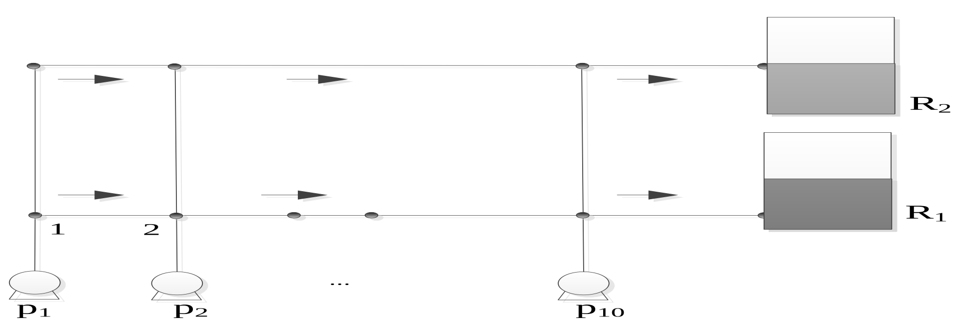


Figure 6.7: A water supply system in case study 2

Table 6.3: Data of reservoirs in case study 2

Tank	Initial head(m)	Minimum head(m)	Maximum head(m)	Surface(m^2)
1	50	42	65	176.715
2	50	42	65	78.538

Table 6.4: Pumping energy costs and maximum number of pump switches

Objective function values ($/day)	Maximum number of pump switches (N_{max})
672.626	5
654.321	10
639.637	15
637.665	20
635.522	25
633.646	-

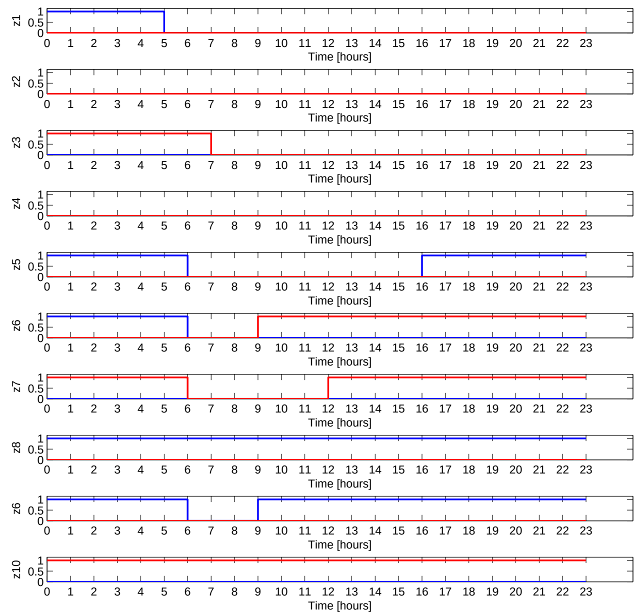
-: without pump switching constraint

6.3.2 Case study 2

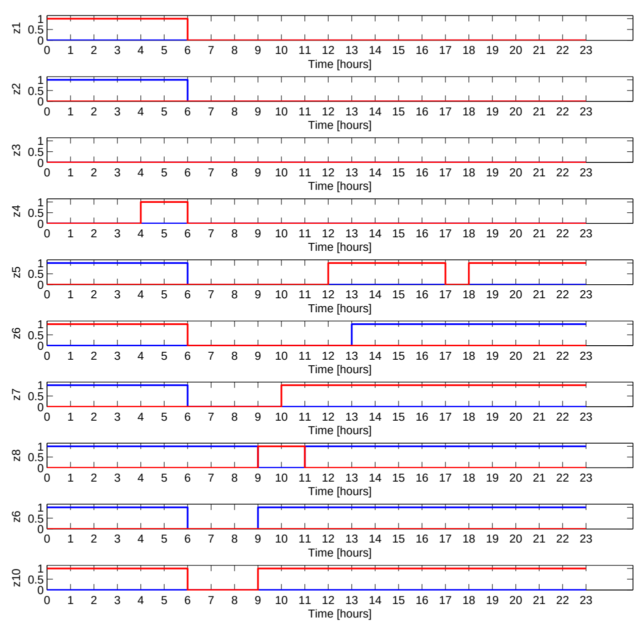
Now we extend the same system considered above with two reservoirs as shown in Fig. 6.7. The data of pumps are the same as used as in case study 1. The data of reservoir 1 and 2 are given in Table 6.3. The base water demands (Q_r) for reservoir 1 and reservoir 2 are assumed to be 0.2(m^3/s) and 0.15(m^3/s), respectively. The formulated MINLP has 480 binary variables, 1007 linear constraints. For solving the problem using GAMS, the time limitation for MINLP is set to 50000.0 (s).

The results of energy costs corresponding to different N_{max} are given in Table 6.4. The optimal pumping schedules for the case N_{max} =10 and N_{max} =20 are shown in Fig. 6.8a and Fig. 6.8b, respectively. The water head trajectories of two reservoirs for different maximum number of pump switches are shown in Fig. 6.9a and Fig. 6.9b, respectively.

Again it can be seen that as the allowable number of pump switches increases, more pumping energy cost is saved. However, the energy cost deceases will be slow (about 2.0($/day)) as the number of pump switches is larger than 15. The optimal pump scheduling uses the pumps located near the reservoirs to be turned on instead of the ones far from the reservoirs as shown in Fig. 6.8a and Fig. 6.8b. Similar to the results from the case study 1, due to the optimized pump scheduling, the pumps are operated intensively to pump water to both reservoirs during low priced tariff periods as shown in Fig. 6.9a and Fig. 6.9b. And the stored water in the reservoirs is supplied to the system by the gravity of reservoirs during the high priced tariff periods; hence it significantly relieves operations of the pumps in these periods.

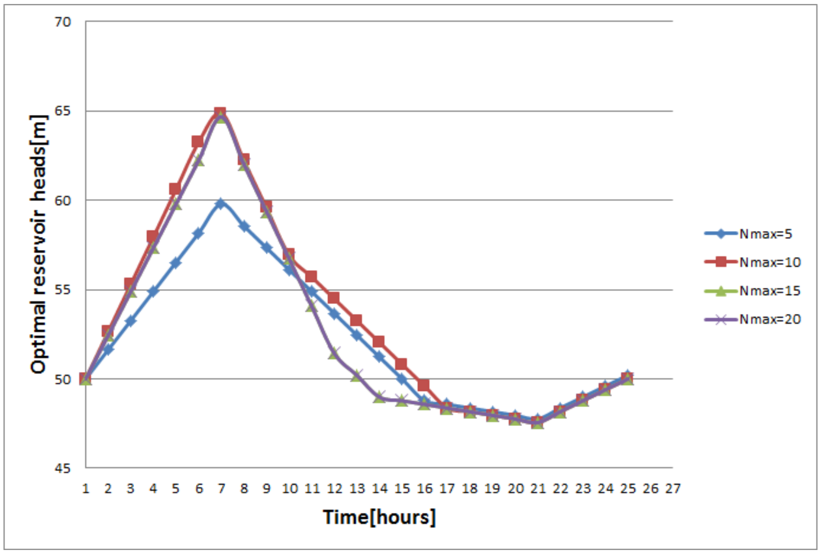


(a) Optimal pumping schedules with N_{max}=10.

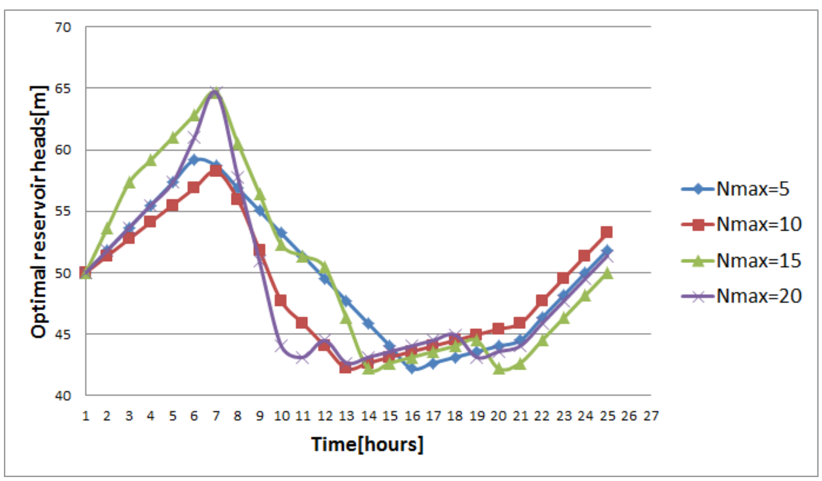


(b) Optimal pumping schedules with N_{max}=20.

Figure 6.8: Optimal pumping schedules



(a) Optimal heads of reservoir 1



(b) Optimal heads of reservoir 2

Figure 6.9: Optimal trajectories for reservoir 1 and 2

Table 6.5: Pumping energy costs and minimum up/down times

LU	LD	Objective function values ($/day)
4	3	635.935
2	3	637.672
2	4	634.262
5	4	644.648
6	2	638.512
2	6	633.557

6.4 Handling the number of pump switches using minimum up and down constraints

The MINLP formulation in the previous section only limits the total number of pump switches of all pumps in the water supply system. There will be a case that a pump will have much number of pump switches, while others have less or a case that a pump has desired number of pump switches, but has high frequency of on/off switching.

The aim of this section is to propose an approach to limit the frequency on/off switching in operations of pumps. To do this, the on/off time periods for pumps is handled by using the minimum up and down constraints [131].

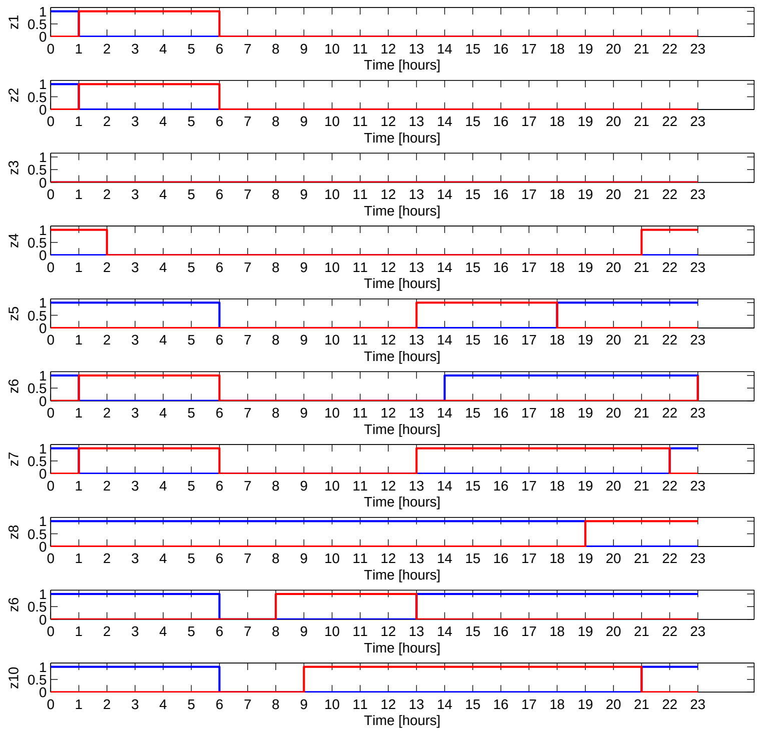
$$z_{i,k} - z_{i,k-1} \leqslant z_{i,\tau}, \quad 2 \leqslant k < \tau \leqslant min\{k + LU_i - 1, T\} \tag{6.22}$$

$$z_{i,k-1} - z_{i,k} \leqslant 1 - z_{i,\tau}, \quad 2 \leqslant k < \tau \leqslant min\{k + LD_i - 1, T\} \tag{6.23}$$

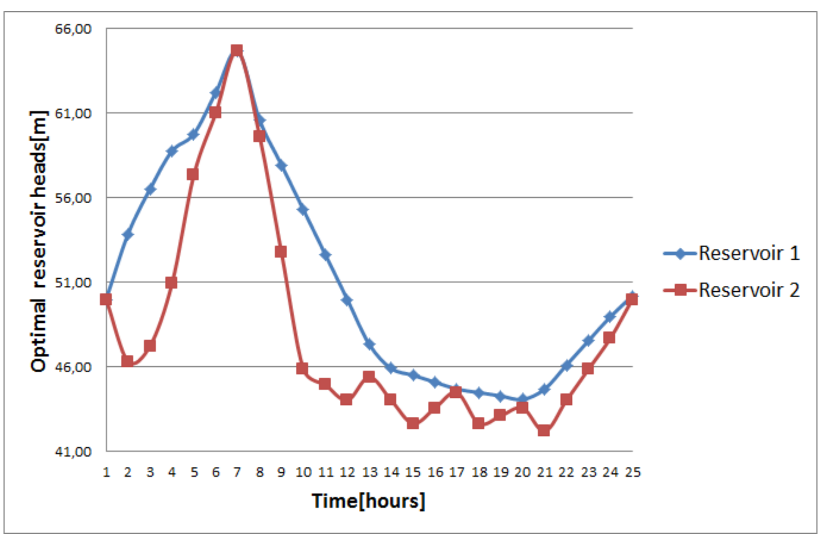
In Eq. (6.22) and (6.23) LD_i and LU_i are given. The constraints ensure that pumps cannot be switched on less than LD_i -1 hours and switched off less than LU_i-1 hours [131]. Now the MINLP problem for optimization of pumping energy and maintenance costs is formulated with the constraints on the number of pump switches in Eq. (6.22) and Eq. (6.23). To evaluate this approach, we take case study 2 into consideration. Numerous MINLP problems are formulated and solved with different values of LD_i and LU_i and the corresponding optimal solutions are given in Table 6.5.

The figure 6.10a and 6.10b represent the optimal operations of pumps and the corresponding optimal head trajectories of two reservoirs for the case LU=5 and LD=4. For the case LU=2 and LD=6, the optimal pump scheduling is shown in Fig. 6.11a, and the corresponding optimal heads of two reservoirs is depicted in Fig. 6.11b.

It can be seen that, due to the optimal pump scheduling, most of pumps will is switched on in the low priced tariff, while they are switched off in the high priced tariff. For this reason, the pumping energy cost is reduced significantly. In addition, the constraints on time periods will lead pump not to switch on/off with high frequency. It is recognized that as we increase the values of LD_i and LU_i, the maintenance cost will reduce while the pumping energy cost will increase.

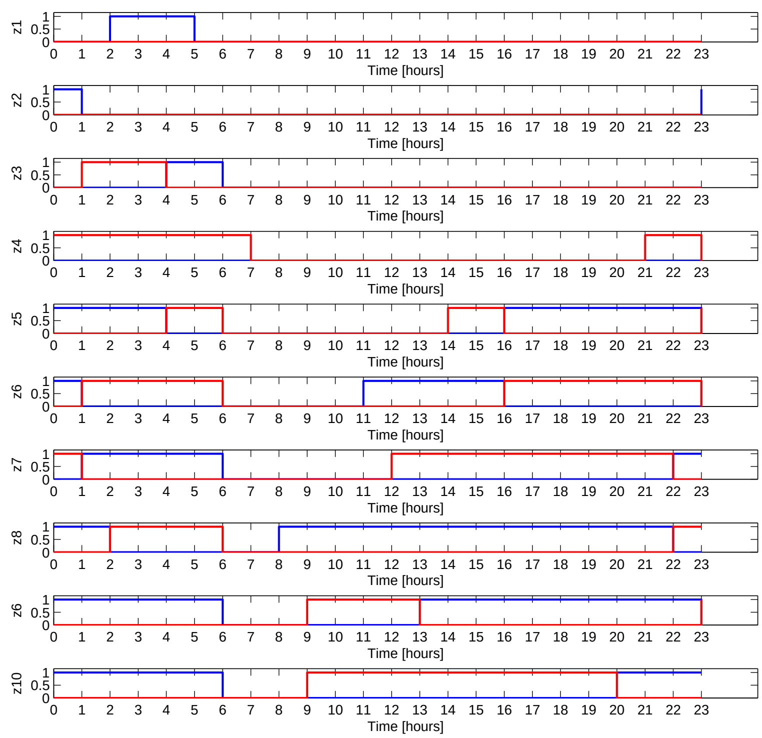


(a) Optimal pump schedules with LU=5, LD=4.

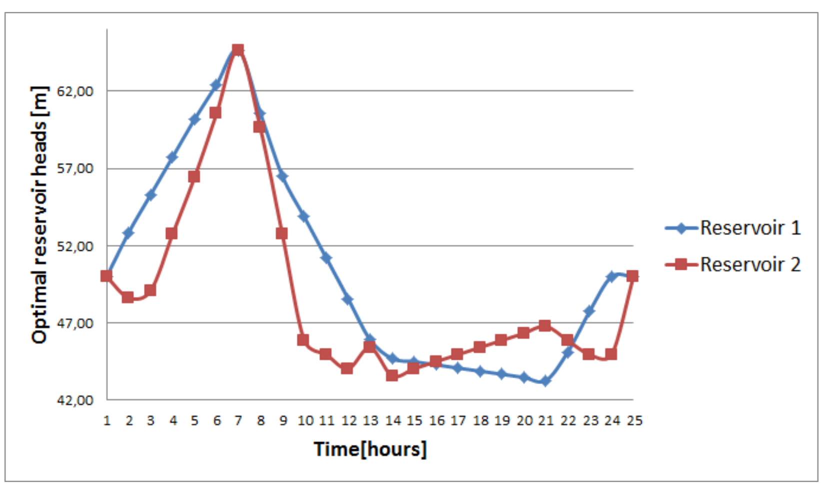


(b) Optimal head trajectories of reservoirs with with LU=5, LD=4.

Figure 6.10: Optimal pump scheduling and reservoir trajectories



(a) Optimal pump schedules with LU=2, LD=6.



(b) Optimal head trajectories of reservoirs with with LU=2, LD=6.

Figure 6.11: Optimal pump scheduling and reservoir trajectories

6.5 Conclusions

In this chapter, we developed a general MINLP model for optimizing the operations of pumps in water supply systems with multiple reservoirs. The optimized pump scheduling will result in a reduction of the pumping energy cost with a user-specified number of pump switches. We proposed to use linear inequalities defining the facets of the feasible MINLP solution for effectively restricting the number of pump switches. In addition, we also considered the minimum up/down time constraints in MINLP problem to handle the number of pump switches for each pump independently. The efficiency of the proposed approach for handling pump switching was demonstrated by determining optimal pump scheduling strategies in two case studies with different scenarios on allowable numbers of pump switches and with different numbers of reservoirs. The introduction of linear inequalities may tighten the formulation of MINLP and help to reduce the computational burden in solving the formulated MINLP problem. This will be further investigated in the future works.

Chapter 7

Optimization operation of water distribution systems

In chapter 6, we have discussed about the operational optimization of water supply systems with multiple reservoirs. This chapter presents an application of a fast and efficient approach, namely the two-stage optimization approach, to solve the optimal pump scheduling problem for a large-scale water distribution system. The optimized pump scheduling results in the reduction of the operating cost while fulfilling the hydraulic as well as operational constraints. In addition, a software package is developed to extract an optimization model from a simulation model in the EPANET environment [58] and solve it by a nonlinear programming solver (e.g., IPOPT in [117]). The software enables users to carry out operational optimizations of WDSs with a minimum effort.

7.1 Introduction

Due to the price increases of electrical energy in the recent years, the energy consumption of pumping takes the most part of the total operating costs of water distribution systems (WDSs). Therefore, minimizing the energy costs while delivering water to meet customer demands is more and more important to water utilities. To reduce the pumping energy consumption, many strategies have been taken such as pump testing, replacing or repairing inefficient pumps, modifying the pump characteristics to match the system, and selecting the best pumps for the application [11]. One of the most effective approaches for reducing the energy consumption is optimal scheduling of the pump operations [12]. A water distribution system comprises of pipes, nodes, valves, and pumps to transport water to customers and services. Water is pumped into the system from sources (e.g., reservoirs) by pump stations as in Fig. 7.1.

Since pumps are embedded in WDSs, the optimization of pump scheduling has to be carried out based on a model describing the whole distribution system. According to the descriptions of hydraulic models, the existing optimization models can be classified into linear programming (LP), mixed-integer linear programming (MILP), mixed-integer

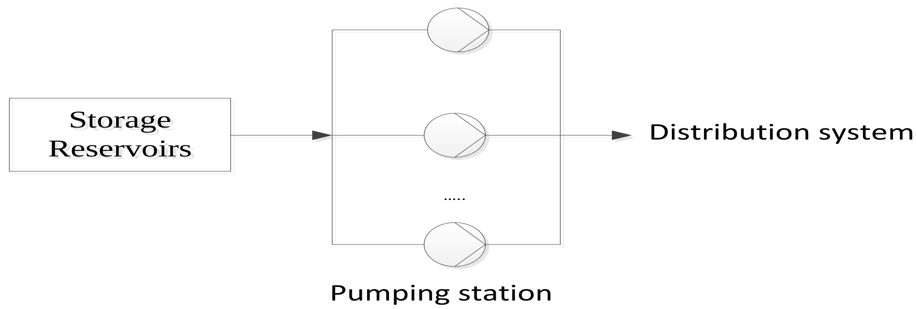


Figure 7.1: A water distribution system [8]

nonlinear programming (MINLP), and simulation based models. The LP and MILP models are either based on mass balance hydraulic relations [16, 17, 71] or derived by linearizing the nonlinear hydraulic equations [65], while the MINLP models are formulated by considering the nonlinear hydraulic equations. The binary variables represent hourly on/off operations of the pumps [8, 18, 43]. The simulation based optimization models are based on a simulation model (e.g. the EPANET model) which allows incorporating if-then-rules for manipulating the operations of pumps and valves. Such models are usually used in conjunction with meta-heuristic algorithms (e.g., genetic algorithms and ant colony algorithms etc.) for carrying out the optimization [12, 20, 70, 89].

To solve the optimal pump scheduling problem, many approaches have been used such as dynamic programming (DP) [61], meta-heuristic genetic algorithm (GA) [20], hybrid GA [70], LP combined with a heuristic algorithm [65, 71], and a two-stage optimization method including NLP combined with local MINLPs in [8, 18] or with a heuristic discretization algorithm in [72], and NLP combined with DP [76]. Although meta-heuristic genetic algorithms are the most generic technique for solving the pump scheduling problems, they cannot be employed easily in online optimizations for large- scale WDSs [43]. This is because they require a large amount of computation time [43].

The two-stage optimization approach has often been applied to solve the MINLP problem for the optimal pump scheduling [8, 18, 43, 68, 72, 80, 127]. In [18], the MINLP problem was relaxed and solved in the first stage. Then, the discrete pump scheduling was found using decomposition method [18] or a heuristic algorithm [72] in the second stage. In [8], it is due to the fact that solving the complete MINLP problem for the whole system was difficult, each pump station is replaced by an aggregated model and the resulting NLP was solved to determine optimal continuous flow and additional head set-points for each pumps station [127]. The on/off operations of individual pumps was determined by solving smaller-scale MINLP problems locally at each pump station to approximate their corresponding continuous flows and heads. It is recognized that the two stage optimization approach is suitable for solving the operational optimizations of large scale WDSs where the interactions between pump stations are small (e.g., small-scale MINLP problems formulated at each pump stations are solved separately to track their continuous flows set-points) and the tank trajectories from a continuous relaxed NLP solution are sufficiently close to optimal tank trajectories of the MINLP solution [43].

The objective of this chapter is to develop a software package which extracts the optimization model from the simulation model in the EPANET environment and carry out the two-stage optimization approach [8, 43] to determine the optimal pump scheduling for large-scale WDSs. At the first stage, the integer variables (e.g., number of pumps in operations for each pump station) are relaxed to the continuous ones, and the NLP problem is solved by a NLP solver to obtain continuous flow set-points for each pump station. At the second stage, a heuristic algorithm is used to translate optimal continuous set-point flows to on/off operations of individual pumps. The accuracy of the on/off pump scheduling is evaluated by EPANET 2 [58].

The remainder of this chapter is organized as follows. Section 7.2 presents the formulation of operational optimization of water distribution systems. Section 7.3 presents a simple heuristic algorithm to deduce 0/1 operations of pumps from the continuous pump station flows. An operational optimization of a real and large-scale drinking water network is given in section 7.4. Conclusions of the paper are provided in section 7.5.

7.2 Problem definition for optimization operation of a water distribution system

Now we formulate an optimization problem in a general form for operations of a WDS. The aim of optimization is to minimize operating costs based on the daily electricity tariff and water demand profile. Consider a WDS including NPU pumps, NP pipes, NJ junction nodes, NT tanks, and NR reservoirs. The time horizon is considered to be T=24 hours and the length of time intervals (Δt_k) is 1 hour. The decision variables are the numbers of switched-on pumps for the pump stations and their normalized speed which then provide optimal flow profiles for each pump station. In the first stage, we relax the integer decision variables (the numbers of switched-on pumps n_p) to continuous variables. The integer solution of the numbers of switched-on pumps will be determined in the second stage optimization [18, 43, 72] in section 7.3

Objective function

Although other forms can be considered, the objective function is defined as the minimization of the energy cost of pump operations

$$\min F = \sum_{k=1}^{T} \sum_{p=1}^{NPU} \gamma\left(k\right) P_p\left(Q_p\left(k\right), n_p\left(k\right), s_p\left(k\right)\right) \tag{7.1}$$

The electrical power consumed by pump station p (P_p) with n_p identical pumps in parallel is calculated by a cubic polynomial [93]

$$P_p = n_p(k)s_p^3(k)\left(A_p\left(\frac{Q_p(k)}{n_p(k)s_p(k)}\right)^3 + B_p\left(\frac{Q_p(k)}{n_p(k)s_p(k)}\right)^2 + C_p\left(\frac{Q_p(k)}{n_p(k)s_p(k)}\right) + D_p\right) \tag{7.2}$$

where A_p, B_p, C_p, D_p are power coefficients for a given pump which can be obtained from interpolating the power-flow data; n_p and s_p are number of pumps switched on and their corresponding relative speeds, respectively. $k = 0, ..., 23$ is the time step.

Equality constraints

At junction node i we have

$$\sum_l Q_{i,l}(k) + d_i(k) = 0;\ i = 1, ..., NJ \tag{7.3}$$

where $Q_{i,l}(k)$ are flows coming or leaving node i, $d_i(k)$ is the demand at node i .

Based on the smoothed hydraulic equation Eq. (3.59) (see [8]), the head loss of pipe l connecting node i and j is described as

$$-H_i(k)+H_j(k)+R_pQ_{i,l}(k)\left(\sqrt{Q_{i,l}^2(k)+a_l^2} + 2b_l + \frac{c_l}{\sqrt{Q_{i,l}^2(k)+d_l^2}}\right) = 0, \quad l = 1, ..., NP \tag{7.4}$$

where R_p, a_l, b_l, c_l, and d_l are calculated according to Eq. (3.60) for each pipe available in the network; $H_i(k)$ and $H_j(k)$ are the head at node i and j, respectively.

The energy conservation of pump station connecting node (inlet) and (outlet) is given in [93]

$$H_i(k) - H_j(k) + a_p\left(\frac{Q_p(k)}{n_p(k)}\right)^2 + b_ps_p(k)\left(\frac{Q_p(k)}{n_p(k)}\right) + c_ps_p(k)^2 = 0 \tag{7.5}$$

where a_p, b_p, b_p are pump head-flow coefficients; p=1,...,NPU

The mass balance for tank i for each time interval (Δt_k) is given by

$$H_i(k+1) - H_i(k) - \left(\frac{\Delta t_k}{S_i}\right)\sum_l Q_{i,l}(k) = 0; i = 1, ..., NT \tag{7.6}$$

where $Q_{i,l}(k)$ is inflow or outflow of tank i; S_i is the cross-sectional of tank i

The head of reservoir i is considered as a constant, i.e.

$$H_i(k) - \overline{H}_i = 0,\ i = 1, ..., NR \tag{7.7}$$

Inequality constraints

Nodal head constraints

$$H_j^L \leqslant H_j(k) \leqslant H_j^U,\ j = 1, 2, ..., NJ \tag{7.8}$$

Pipe/link flow constraints connecting node i

$$Q_{i,l}^L \leqslant Q_{i,l}(k) \leqslant Q_{i,l}^U,\ l = 1, ..., NP \tag{7.9}$$

Head constraints in the tanks

$$\begin{array}{l} H_i^L \leqslant H_i(k) \leqslant H_i^U \\ |H_i(T) - H_i(0)| \leqslant \Delta_i \end{array} \tag{7.10}$$

where Δ_i is the allowable deficiency of the water tank level at the end of a day.

Flow constraints and the constraints of normalized speed of pumps in pump station p [43]

$$Q_p(k) - \widetilde{Q}_p n_p(k)\, s_p(k) \leqslant 0 \tag{7.11}$$

$$s_p^L \leqslant s_p(k) \leqslant s_p^U \tag{7.12}$$

$$n_p^L \leqslant n_p(k) \leqslant n_p^U \tag{7.13}$$

where $\widetilde{Q}_p$ is the pump cutoff flow.

Constraints on the changes of pump station flows between two successive time intervals

$$|Q_p(k) - Q_p(k+1)| \leqslant \Delta_p; p = 1, ..., NPU \tag{7.14}$$

In summary, the above problem can be formulated as the following general NLP form

$$\begin{array}{ll} \min & \Phi(\mathbf{x}, \mathbf{u}) \\ s.t. & \mathbf{g}(\mathbf{x}, \mathbf{u}) = \mathbf{0} \\ & \mathbf{h}(\mathbf{x}, \mathbf{u}) \leqslant \mathbf{0} \\ & \mathbf{x}^L \leqslant \mathbf{x} \leqslant \mathbf{x}^U \\ & \mathbf{u}^L \leqslant \mathbf{u} \leqslant \mathbf{u}^U \end{array} \tag{7.15}$$

The decision variables **u** include the numbers of switched-on pumps in the pump stations and their relative speed. Thus the total number of decision variables is NPU×2×T. The state variables **x** include the pipe flows and node heads and therefore the total number of state variables is (NP+NJ+NT+NR)×T. The number of equality constraints g is equal to the number of state variables. In addition, there are a large number of inequality constraints.

As a result, an optimal operation problem of a WDS leads to a large-scale NLP which should be solved in an efficient way. Here we use a simultaneous solution framework, i.e. both the decision and state variables in the whole time horizon are considered as optimization variables. And both equality and inequality constraints in the whole time horizon are treated as constraints of the NLP problem [132]. The IPOPT software [117] is used as the nonlinear optimization solver. In each iteration, values of the objective function, the equality and inequality constraints and their gradients are computed and delivered to IPOPT which will then update the optimization variables for the next iteration. The solution procedure will converge when the optimality conditions in IPOPT are satisfied, which then will provide optimal operation strategies for the WDS. Since the function values and gradient values are exactly computed, this approach can be considered as being highly efficient. The solution procedure will converge when the optimality conditions in IPOPT are satisfied, which then will provide optimal operation strategies for the WDS. Since the function values and gradient values are exactly computed, this approach can be considered as being highly efficient.

7.3 Discrete pump scheduling

The two-stage optimization is proposed in Fig. 7.2 where the first stage is to determine the continuous pumping schedule for each pump station by solving the NLP problem as in section 7.2. The second stage is to calculate discrete pumping schedules for pump stations so as to approximate the continuous solution [8, 18, 43, 68]. It is due to the fact that a fractional number of pumps switched on will be carried out by a sequence of integer number of pump switched on in smaller time intervals [68, 72]. Here, in the second stage, we employ a heuristic procedure [72] to calculate integer number of pumps switched on from the fractional number of pump switched on. To do this, the time interval (e.g., Δt_k=1 hour) is divided into several smaller time intervals which are referred to as *discretized time intervals* (Δt_{k_d}). k_d is the time step of the discretized time interval Δt_{k_d}. The number of pumps switched on in a discretized time intervals (e.g.,Δt_{k_d}) is calculated by the method proposed in [72]. At first, in each time interval k_d, the number of switched-on pumps is assigned to $\lfloor n_p \rfloor$. Then, additional number of switched-on pumps are calculated as Δn_d

$$\Delta n_d = \left\lfloor frac\left(n_p\right) \frac{\Delta t_{k_c}}{\Delta t_{k_d}} + 0.5 \right\rfloor \tag{7.16}$$

where $frac\left(n_p\right) = n_p - \lfloor n_p \rfloor$; $\lfloor n_p \rfloor$ is the floor rounding of n_p.

In addition, we deduce the discrete pump scheduling for each pump station so that total flows resulted by it in each of tariff time periods will approximate the total continuous flows in the same tariff time periods. The reason lies in the fact that pump scheduling

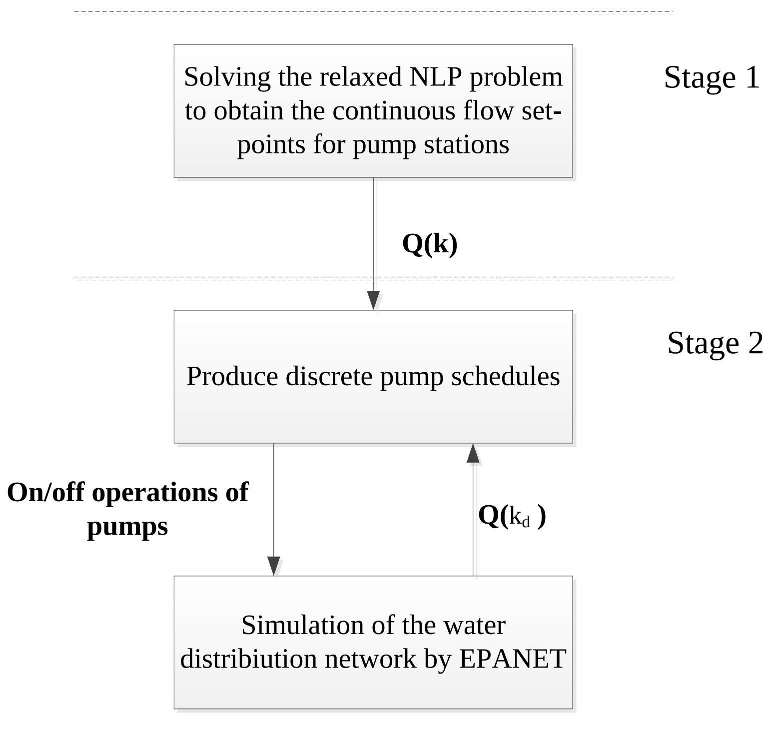


Figure 7.2: Dicretize the continuous pump schedules

varies significantly according to electrical tariff periods [72]. For a electrical time period tp_j, we expect that

$$TFL_{i,tp_j}^{d} \simeq TFL_{i,tp_j}^{c} \tag{7.17}$$

where $TFL^{d}\left(tp_j\right)$ is the total flow of pump station i resulted by discrete pump scheduling over the time period of tp_j and; $TFL^{c}\left(tp_j\right)$ is the total continuous flow of pump station i. The total discrete and continuous flows can be calculated as

$$TFL_{i,tp_j}^{d} = \sum_{k_d} Q_i\left(k_d\right)\Delta t_{k_d} \tag{7.18}$$

and

$$TFL_{i,tp_j}^{c} = \sum_{k} Q_i\left(k\right)\Delta t_{k} \tag{7.19}$$

where $Q_i\left(k_d\right)$ and $Q_i\left(k\right)$ are flows resulted from dsicrete pump scheduling (EPANET) and continuous set-point flows, respectively.

To minimize the deviation between TFL_{i,tp_j}^{d} and TFL_{i,tp_j}^{c}, the simple way is to use a small refined discrete time interval (Δt_{k_d}). However, this may lead pump switching

Table 7.1: The basic heuristic algorithm

Initialization: the water distribution system file in EPANET.
Solve the relaxed NLP to calculate the continuous flow set points for pump stations (TFL^c_{i,tp_j})
for i=1: NPU
  for j=1:N_{tp}
   while $(abs(TFL^d_{i,tp_j} - TFL^c_{i,tp_j}) > \Delta_{tp})$
      if$(TFL^d_{i,tp_j} < TFL^c_{i,tp_j})$
       $n_i = n_i + 1.$
      else
       $n_i = n_i - 1.$
      end if
      Simulation the WDS with the modified discrete pump scheduling to calculate TFL^d_{i,tp_j}.
   end while
  end for
end for .

on/off in many times. For this reason, the value of Δt_{k_d} should be chosen appropriately. Here, we choose $\Delta t_{k_d} = 10$ minutes.

We also use a heuristic algorithm to further modify the discrete pumping schedules in Eq. (7.16) so as to reduce the deviation in Eq. (7.17). The modification is made for successive discrete time intervals (Δt_{k_d}). For example, if the continuous flow set-point of a pump station is larger than the discrete flow in a tariff time period (tp_j), additional pumps will be switched on. Also in the case, if all pumps in a pump station has been already switched on at a specified discretized time step k_d, additional pumps will be switched on in the next discretized time step k_d+1. This procedure continues until $TFL^d_{i,tp_j} \simeq TFL^c_{i,tp_j}$ is reached. The basic algorithm is given in Table 7.1 in which n_i is the number of pumps switched on in each pump station, Δ_{tp} is the flow tolerance over a tariff time period tp, and N_{tp} is the number of electrical tariff time periods. It is noted that for variable speed pump stations the algorithm only modifies the number of pumps switched on while keeping the pump relative speeds the same as those found in the continuous solution [72].

The brief description of the software package is given in the appendix D. The software package extracts the optimization problem from the simulation model described in EPANET 2 [58], solves the optimization problem using a NLP solver, and produces the on/off pumping schedule using the heuristic algorithm described above. For a water distribution system described by a file in EPANET, with our developed software package, users only need to define the electrical tariff, deviation of the final tank levels, bound constraints for optimization variables (flows, heads, number of pump switched on, and relative speeds), then the relaxed NLP in section 7.2 and the heuristic algorithm are implemented automatically .

7.4 Case study: Optimization of a real drinking water distribution network

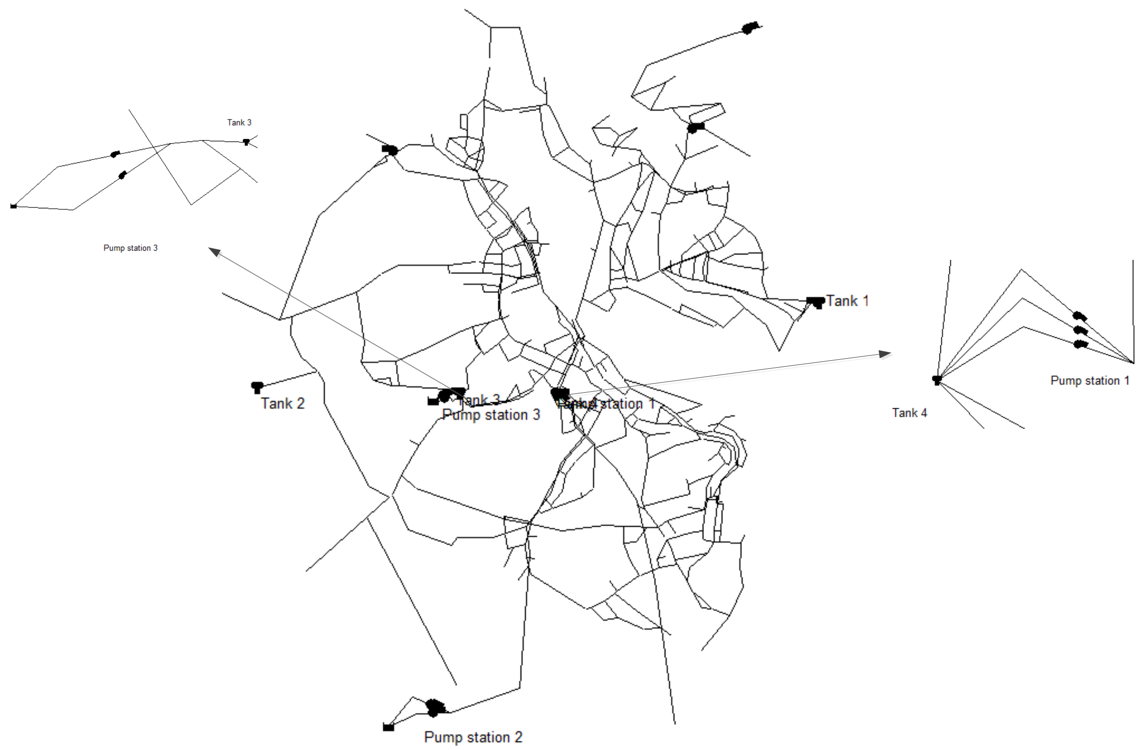


Figure 7.3: Schematic description of the drinking water network of Hof city.

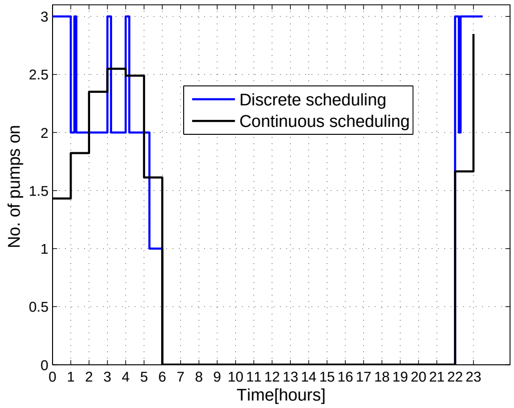
In this section, we apply our modeling and optimization approach to a real WDS of Hof city in Germany (the EPANET file of the system is taken from group of water supply and waste water treatment in [133]). The WDS is schematically depicted in Fig. 7.3. The network consists of 790 pipes, 643 nodes, 4 storage tanks, 4 single speed booster pumps, 3 pump stations, and 2 reservoirs. The total length of the main pipes is 133.561 km and their diameters range from 80mm to 600mm. Pump station 1 and 3 have three and two identical fixed speed pumps, respectively, while pump station 2 has two identical variable speed pumps. The pipe roughness coefficients for all pipes are estimated to be 1mm. Due to space limitation, detailed data of pipes and nodes are not given, only physical characteristics of the pumps and tanks are listed in Tables 7.4 and 7.3. An available EPANET simulation model is used to extract the network data for establishing the optimization model. For the pipe hydraulic relation, the smoothed head loss model proposed in [8] is used instead of the Darcy-Weisbach equation. The lower and upper bounds of the variables are specified based on their physical ranges. For formulating the cost function, a changing daily electricity tariff shown in Fig. 7.7a is considered. In addition, we consider a daily total demand scenario given from the network operation of the city, also as shown in Fig. 7.7b. The deficiency of water tank level at the end of day is set to 0.01m for all tanks and the lower and upper bounds of the normalized speed of pumps are specified as 0.6 and 1.0, respectively. The details of the NLP problem are given in Table 7.2. Computations for solving the optimization problem were performed using diverse initializations for the optimization variables. It took less than 2 minutes for running the optimization on an Intel (R) Core (TM) i7-2600 CPU 3.4GHz 12GB RAM desktop. The heuristic algorithm took 125.6 s to derive the discrete pump scheduling from the continuous one. The continuous flow set points and corresponding discrete flows are shown in Fig. 7.5. In Table 7.2, it can be seen that

Table 7.2: The property and results of the optimization problem in the case study

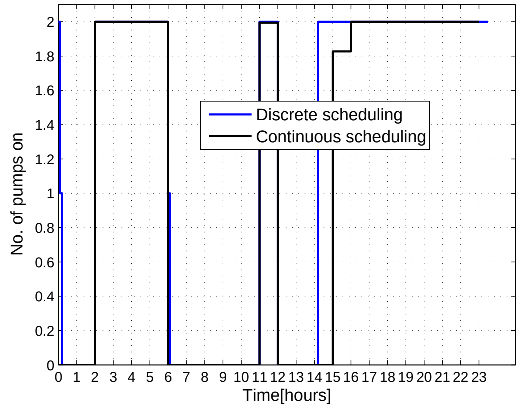
Total number of variables	34608
Total number of equality constraints	34512
Total number of inequality constraints	333
CPU time (s)	76.71
Objective function value with continuous pump scheduling (€)	1178.47
Objective function value with discrete pump scheduling(€)	1263.30

the objective function value resulted by the discretized pump scheduling is higher than the one resulted by the continuous solution.

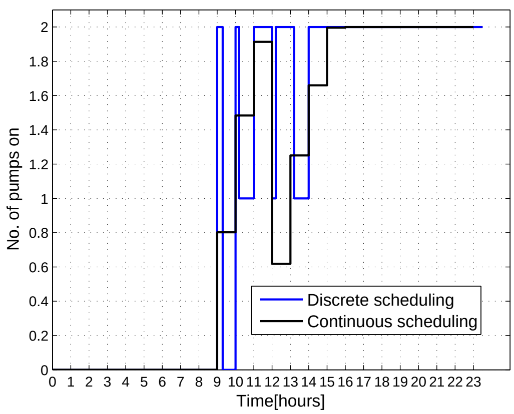
The discrete pump scheduling and the corresponding tank heads are shown in Fig. 7.4 and Fig. 7.6, respectively. Tank 4 has the largest diameter and lower initial head as compared to that of tank 2 and tank 3. Tank 3 locates near the water source. Therefore, the optimal schedule will enable pump station 1 to pump water heavily from tank 4 to supply for the network and the other tanks during the low tariff from midnight to 6:00 a.m., as seen in Fig. 7.4a. As shown in Fig. 7.4b, pump station 2 also operates in the full capacity during the low tariff from 2:00 a.m. to 6:00a.m. to withdraw water from the reservoir to the system. As a result, the tank heads in tank 1, 2, and 3 rise during this period, as shown in Fig. 7.6a, 7.6b and 7.6c. Since tank 3 has the highest initial tank head and the second largest diameter, much more water is reserved in tank 3 during the low tariff period. Due to the tariff increase from 6:00 a.m., tank 4 starts filling and all pump stations are switched off for a certain time period, as shown in Fig. 7.4. In this period, tank 1 and 3 supply water to the network and to tank 2 and 4. From 10:00 to 22:00 the tariff has the highest level, the optimal operation utilizes the reserved water in the tanks as much as possible. This can be seen in Fig. 7.6 where all tanks except for tank 4 supply water to the network. However, the optimal operation must ensure that the tank level at the end of the day will return to the tank level at the beginning of the day. For this reason, pump station 2 and 3 have to operate during the high tariff time period to fill water to tank 3 and tank 4. After 22:00 all pump stations are switched on due to the low tariff and thus the tank levels finally approach to the specified values.



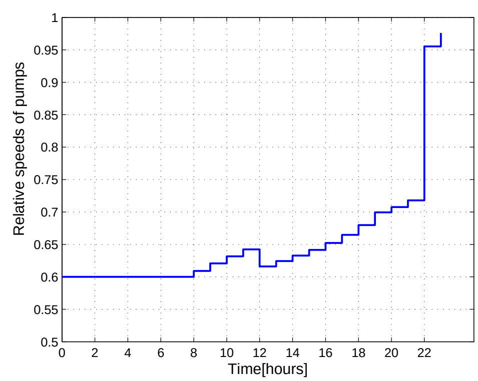
(a) Pump station 1



(b) Pump station 2



(c) Pump station 3

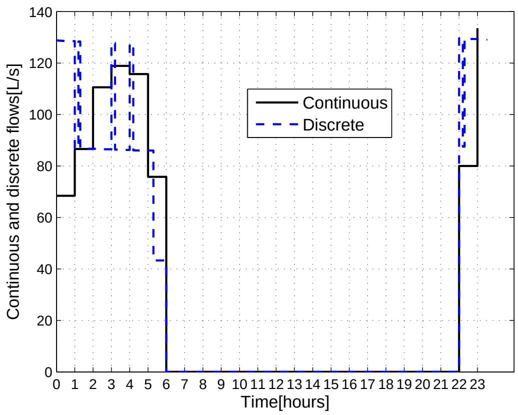


(d) Speed of pumps in pump station 3

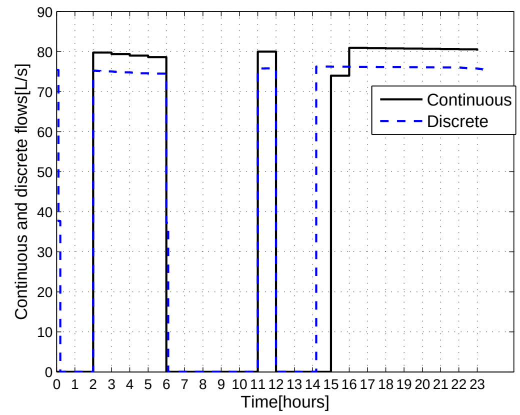
Figure 7.4: Continuous and discrete pump scheduling

Table 7.3: Data of storage tanks for the case study

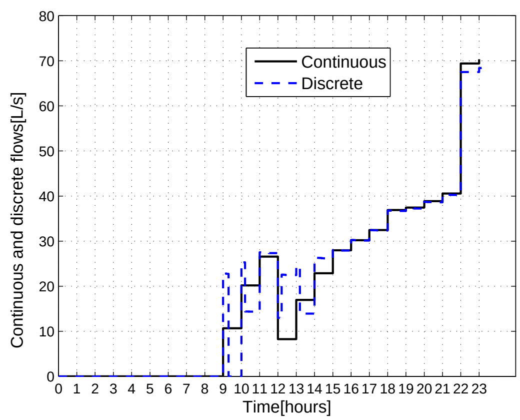
Tanks/reservoirs	Initial head (m)	Minimum head (m)	Maximum head (m)	Surface (m2)
1	510.0	509.0	512.0	380.1
2	514.0	512.0	517.0	350.0
3	516.0	514.0	518.0	580.0
4	512.0	509.0	513.0	920.0
Reservoir 1&2	Fixed head: 480.0			



(a) Pump station 1



(b) Pump station 2

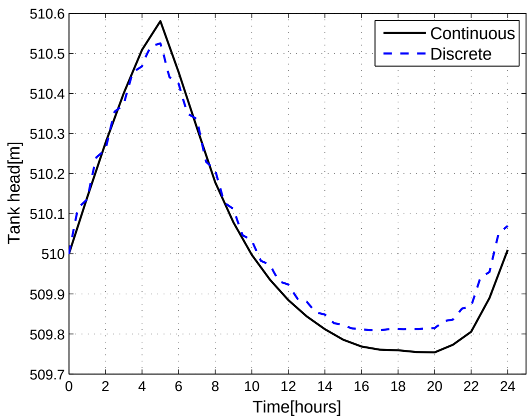


(c) Pump station 3

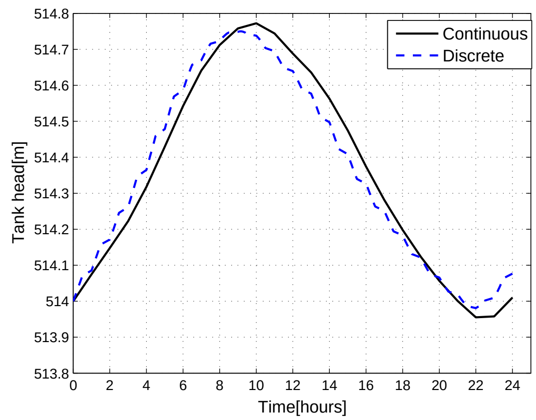
Figure 7.5: Continuous and discrete pump station flows

Table 7.4: Pump station data for the case study

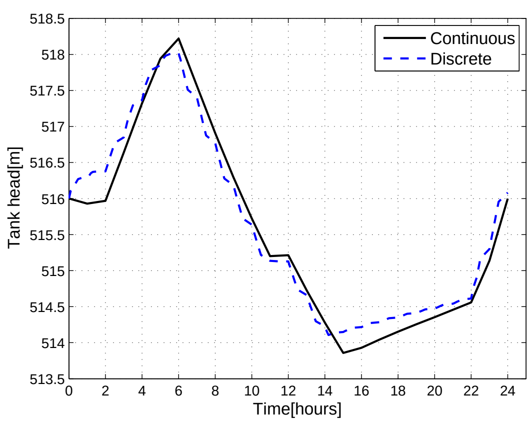
Pump station	Hydraulic coefficients				Power coefficients			
1,2,3	a_p	b_p	c_p	$\widetilde{Q}_p$	A_p	B_p	C_p	D_p
	-0.002344	96.0	2.8	49.0(l/s)	$-5.6E-4$	$25E-3$	0.37	11.79



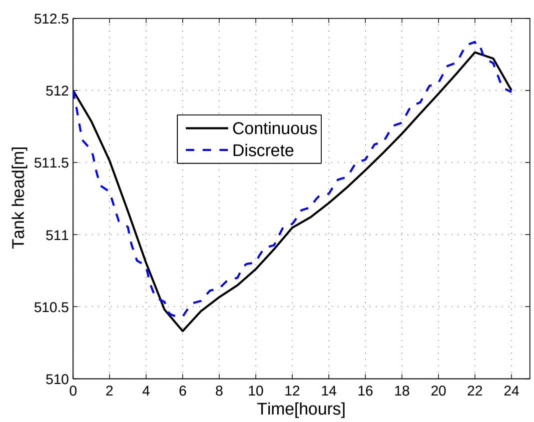
(a) Tank 1



(b) Tank 2

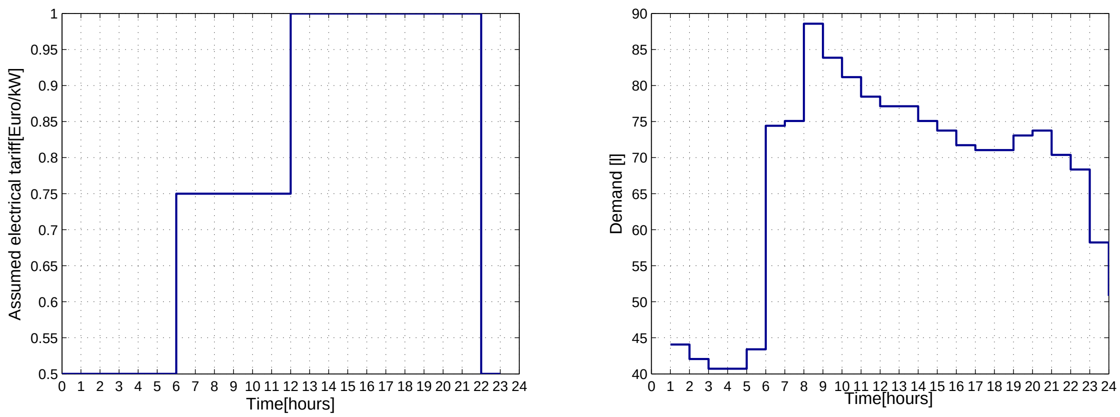


(c) Tank 3



(d) Tank 4

Figure 7.6: Continuous and discrete tank trajectories



(a) Electrical price tariff

(b) Daily profiles of water demand

Figure 7.7: Daily demand and electrical tariff

7.5 Conclusions

In this chapter we present a systematic way to carry out optimization of large-scale WDSs. A two-stage optimization approach is used to determine the on/off optimal pumping schedules in which the relaxed NLP is solved to provide continuous flow set-points for pump stations while the on/off operations of individual pumps are translated from the continuous flow set points using a heuristic algorithm. To carry out the optimization problem in such an efficient manner, we also develop a software package for formulating and solving the optimization problem automatically. This enables water utilities to optimize operations of WDSs with a minimum effort. The results from carrying out of operational optimization of a real and large scale drinking water distribution system have shown that the operation strategy provided by the optimization enables the water system to minimize the operating costs while keeping the specified operating constraints. Besides the advantages of the approach such as it can solve the pump scheduling problems for large-scale WDSs in a short computation time, necessary conditions should be investigated to ensure that the continuous solution of the relaxed NLP is practical (e.g., relaxed continuous pump flows must lies in a feasible range like $Q_p \in \{0\} \cup \left\{Q_p^L, Q_p^U\right\}$) and it can be implemented by on/off operations of individual pumps in each pump station.

Chapter 8

Conclusions and future works

8.1 Conclusions

Globally climatic changes, droughts, and high temperatures have led to shortages of water sources and water restrictions in many locations over the world. Moreover, the population, economic, manufacturing, and industrial growth significantly affect the ability of water systems to deliver sufficient water. A water loss control program is therefore necessarily developed in order to lessen the severity of the effects of drought and climate change on water systems by retention of more water in their distribution system. This will retain more water for the customers on one hand and decrease the amount withdrawn from water sources on the other hand [134]. Nowadays, many water utilities have been developing control strategies to reduce water losses to an economic and acceptable level so as to preserve valuable water resources and to relieve operating and maintenance costs [42].

This thesis developed efficient solution approaches for solving the optimal pressure management to reduce leakage in water distribution systems and the optimal pump scheduling to reduce pumping energy and maintenance costs in water supply and distribution systems. Our contributions are summarized as bellows

- First, mathematical program with complementarity constraints (MPCC) was proposed to solve the MINLP problem for optimal localization of PRVs in large-scale water distribution systems. In addition, a novel rounding scheme is developed to improve the quality of optimal solution as well as accelerate the MPCC solution procedure. The MPCC approach has been applied for two benchmark water distribution systems in the literature and the results reveal new optimal locations of PRVs which result in higher decrease of leakage flows and excessive pressure reduction as compared with those given in the literature.

- Second, it is due to the fact that the existing PRV model is described by a two-mode model. This model cannot account the check valve mode for preventing reverse flows when the upstream pressure of a PRV is lower than its downstream pressure. In this thesis, an extended PRV model representing fully operation modes of PRVs was introduced. Then, this model was applied to solve the optimal pressure regulating problems in water distribution systems. Numerical experiments have revealed that the extended PRV model outperforms the existing ones in both accuracy and quality of optimal solutions.

- Third, a general MINLP problem was formulated to minimize the pumping energy cost and, at the same time keep the maintenance cost at certain levels. A set of linear inequality constraints was proposed to handle the number of pump switches instead of using the non-smooth constraints as in the literature. In addition, restriction on the number of pump switches can be accomplished by limiting the total number of pump switches of all pumps in the water system or by limiting on/off time periods of each pump.

- Fourth, optimal pump scheduling problem in a water distribution system was formulated as a MINLP problem. Due to difficulties in solving such the MINLP by available MINLP solvers, we proposed to apply a two-stage optimization approach to solve the optimal pump scheduling for a real and large scale drinking water distribution network in which the relaxed NLP is solved in the first optimization stage to determine the flow set-points while the discrete on/off operations of individual pump in each pump station are deduced in the second optimization stage to approximate the set point flows using a simple heuristic algorithm. In addition, a software package was also developed in C language in order to formulate and solve the optimization problem automatically.

8.2 Future works

In water distribution systems, pumps are scheduled to deliver water with sufficient flow and pressure quantities to customers and services. In addition, the water quality is required to meet the standard. Therefore, optimal planning and managements of WDSs have to take the water quality factor into consideration. The future works will concentrate on following research aspects:

- Modeling of water quality as well as introducing it into the optimization problem for optimal operations of water distribution systems.

- Developing a model predictive control to water loss reduction.

- Developing a fast optimization algorithm in order to control water distribution systems efficiently.

Chapter 9

Appendix

A Optimization tasks and optimization methods

Optimization of pressure managements to leakage reduction and operational optimization of pumps to reduce pumping energy and maintenance costs are addressed in this thesis. A brief explanation of these problems is given as bellows:

- The optimization of pressure management is to minimize excessive pressure of the system by optimizing operations of control valves (e.g., pressure reducing valves) in WDSs. It is necessary to distinguish two optimization problems to be solved 1) optimization of the locations of control valves in the water distribution system and 2) optimization of operations of control valves in the water distribution system where the their locations have been already determined. The optimal localization of control valves is formulated as a mixed integer nonlinear programming (MINLP) since the binary variables are introduced to each link to indicate whether a control valve is placed on the link or not [35]. For a water distribution system where valves have already been installed, the optimization of pressure management is casted as a nonlinear optimization problem (NLP) [37] in which the pressure settings of valves (or valve openings) are decision variables. In this NLP problem, the model of control valves is critical to the quality of optimal solutions.

- Operational optimization of a WDS to minimize the pumping energy while keeping the maintenance cost at certain levels is achieved by scheduling on/off operations of pumps. To represent on/off operations of pumps, binary variables are introduced. Therefore, the optimal pump scheduling is casted as a mixed integer nonlinear programming (MINLP) [18]. A MINLP solver is used to solve the optimization problem.

B Optimization algorithms used in this thesis

In this thesis, MINLP and NLP algorithms are used to solve the formulated optimization problems. In particular, the MINLP problem is solved by using MINLP algorithms integrated in BONMIN solver [135] or by the mathematical program with complementarity constraints (MPCC) approach, while the NLP problem is solved by a NLP solver such as IPOPT [117]. A brief introduction to these algorithms is given as bellows:

B.1 Nonlinear algorithms

The nonlinear optimization algorithms can be interior point (IP), sequence quadratic programming (SPQ). In this thesis, we use the IP algorithm in the IPOPT solver [117] to solve the NLP problem. IPOPT solver can solve large scale NLP problems efficiently [132, 136] and it can perform well as a NLP solver for the MPCC solution approach [137]. Here we briefly describe the IP algorithm. The general NLP problem is given in Eq. (9.1)

$$\begin{aligned} &\underset{x \in \Re^n}{min}\, f(x) \\ &\text{s.t.} \\ &g(x) = 0 \\ &x_L \leqslant x \leqslant x_U \end{aligned} \tag{9.1}$$

The IP algorithm follows a barrier approach in which the bound constraints are replaced by logarithmic barrier terms which are added to the objective function [132]

$$\begin{aligned} &\min\ \varphi(x) = f(x) - \mu \sum_{i=1}^{n} \ln\left(x^{(i)} - x_L^{(i)}\right) - \mu \sum_{i=1}^{n} \ln\left(x_U^{(i)} - x^{(i)}\right) \\ &\text{s.t.} \\ &g(x) = 0 \end{aligned} \tag{9.2}$$

where $\mu > 0$ is a barrier parameter. It can be seen that the objective function of the barrier problem becomes arbitrarily large when $x^{(i)}$ approaches either of its bounds so that a local solution of the barrier problem $x_*(\mu)$ lies in the interior of bounds, i.e., $x_L \leqslant x \leqslant x_U$. Under mild conditions, a local solution $x_*(\mu)$ converges to the solution of the original NLP problem as $\mu \to 0$ [132]. Therefore, a strategy for solving the original NLP problem is to solve a sequence of barrier problems with decreasing barrier parameters μ_l, where l is the counter for the sequence of subproblems. In addition, to solve the barrier problem, IPOPT uses a primal-dual approach and applies the Newton method with a novel filter line search strategy for solving the Karush-Kuhn-Tucker condition [117, 132].

B.2 Mathematical program with complementarity constraints (MPCC)

MINLP problems can be reformulated into a mathematical program with complementarity constraints (MCCC) [39, 50] in which binary variables are relaxed and the binary constraints (e.g., $\mathbf{y} = \{\mathbf{0}, \mathbf{1}\}$) are replaced by complementarity constraints in the MPCC. We consider a general MPCC problem given in Eq. (9.3)

$$\begin{aligned}
&\min \ f(x, y) \\
&\text{s.t.} \\
&h(x, y) = 0 \\
&g(x, y) = 0 \\
&x, y \geqslant 0 \\
&0 \leqslant x_i \perp y_i \geqslant 0, \quad i = 1, ..., nc
\end{aligned} \tag{9.3}$$

Since obtaining solutions to complementarity constrained NLPs pose a challenge, MPCCs usually fail to satisfy constraint qualifications such as linear independence of constraint gradients and Mangasarian Fromovitz constraint qualification, commonly assumed to hold for NLPs [40, 138]. There are two most efficient formulations of MPCC [40, 41, 137]: Reg(ε) regularized formulation in Eq. (9.4), and PF(ρ) penalty formulation in Eq. (9.5), respectively.

$$\begin{aligned}
&\min \ f(x, y) \\
&\text{s.t.} \\
&h(x, y) = 0 \\
&g(x, y) = 0 \\
&x, y \geqslant 0 \\
&x_i y_i \leqslant \varepsilon, \quad i = 1, ..., nc
\end{aligned} \tag{9.4}$$

$$\begin{aligned}
&\min \ f(x, y) + \rho x^T y \\
&\text{s.t.} \\
&h(x, y) = 0 \\
&g(x, y) = 0 \\
&x, y \geqslant 0
\end{aligned} \tag{9.5}$$

It is noted that a complementarity constraint (e.g., $0 \leqslant x_i \perp y_i \geqslant 0$ or $x_i y_i = 0$) can be replaced by a nonlinear complementarity problem function (NCP) such as the Fischer-Burmeister function in Eq. (9.6) for efficient computation [139].

$$\phi_i(x_i, y_i) = x_i + y_i - \sqrt{x_i^2 + y_i^2} \tag{9.6}$$

In particular, the constraint $\phi_i(x_i, y_i) \leqslant \varepsilon$ can be used for the constraint $x_i y_i \leqslant \varepsilon$ in Eq. (9.4) . Similarly, the penalty function $\rho \sum_i \phi_i(x_i, y_i)$ can be used for the penalty function $\rho x^T y$ in Eq. (9.5). The solutions of NLPs are called stationary points which converge to a final solution, called a limit point of the MPCC.

In regularized formulation, the complementarities are relaxed with a positive relaxation parameter ε, and the MPCC solution can be obtained by solving a sequence of relaxed

NLPs with decreasing relaxation parameter ε [137]. In contrast to the regularized formulations, in the penalty formulation, complementarities are added to the objective function and the resulting NLP problem is solved for a particular value of ρ or by a sequence of NLP problems with increasing penalty coefficients ρ [40, 41]. The penalty reformulation is more reliable than the regularized reformulation since the complementarity constraints are not included as constraints but only in the objective function, so that the problem size is maintained despite the complementarities [137]. In addition, the MPCC solution can be obtained by solving the relaxed NLP in a single time instead of multiple times, if an appropriate value of ρ is chosen [41, 137, 140]

C MINLP algorithms

The basic MINLP algorithms for solving the MINLP problem given in Eq. (9.7) are branch and bound and outer approximation methods. The MINLP algorithms have been developed for many years based on two basis algorithms to solve MINLP problem efficiently. For example, there are several algorithmic choices that can be selected with BONMIN [135], namely, B-BB is a NLP-based branch-and-bound algorithm, B-OA is an outer-approximation decomposition algorithm, B-QG is an implementation of Quesada and Grossmann's branch-and-cut algorithm, and B-Hyb is a hybrid outer-approximation based branch-and-cut algorithm [130]. In this section, we briefly present basic algorithms of branch and bound and outer approximation methods.

$$
\begin{aligned}
&\underset{x,y}{min}\, f\left(x,y\right)\\
&s.t.\\
&g\left(x,y\right)\leqslant 0\\
&x\in X, y\in Y
\end{aligned}
\tag{9.7}
$$

C.1 Branch and Bound method

The fundamental idea is to subdivide the original MINLP into subproblems. The reason is due to the fact that the original problem is difficult to solve as a whole. The solutions of these subproblems yield optimal solution for the original MINLP problem. The process of subdivision is generally referred to as the branching strategy [141, 142, 143]. Let z^U is the best current upper bound on the optimal solution value of MINLP problem. At each stage in the solution process, a search strategy is used to select an unsolved subproblem $P^{(k)}$ at node k

$$\begin{aligned} P^{(k)} \quad & \underset{x,y}{min}\, f\left(x,y\right) \\ & s.t \\ & g\left(x,y\right) \leqslant 0 \\ & x^L \leqslant x \leqslant x^U \\ & y^L \leqslant y \leqslant y^U \end{aligned} \tag{9.8}$$

There are following four cases:

1. if $P^{(k)}$ is infeasible, then this node is eliminated by infeasibility
2. if $P^{(k)}$ is feasible, and if $f\left(x^k, y^k\right) > z^U$. The node is pruned by bound.
3. if $P^{(k)}$ is feasible, and if y is integer, and if $f\left(x^k, y^k\right) < z^U$. The upper bound $z^U$is updated by $f(x^k, y^k)$ and the node is pruned by optimality.
4. if $P^{(k)}$ is feasible and $f\left(x^k, y^k\right) < z^U$, and y_i^k is not integer. In this case node k is further subdivided into two new subproblems corresponding to two new nodes [143].

The solution process (a search strategy, subdivision, and elimination) continues until all subproblems are fathomed.

C.2 Outer approximation method

The outer approximation (OA) algorithm alternates between solving a MILP problem and one or two NLP problems [143, 144]. The main idea is to linearize a MINLP to a MILP problem at a set of linearization points [143, 144]. The formulated MILP is solved to obtain an integer solution. The integer solution is fixed and the MINLP problem becomes a NLP problem. If the NLP solution is feasible, the solution will be added to the set of linearization points and they are used for next linearization, otherwise another NLP is formulated to minimize the violation of constraints. The solution of this NLP is also added to the set of linearization points $T = \{(x^0, y^0), (x^1, y^1), ..., (x^n, y^n)\}$. The

MILP problem is formulated using linearization

$$\begin{aligned}
&\min_{\alpha,x,y} \alpha \\
&\text{s.t.} \\
&\nabla f\left(x^k, y^k\right)^T \begin{pmatrix} x - x^k \\ y - y^k \end{pmatrix} + f\left(x^k, y^k\right) \leqslant \alpha \\
&\nabla g\left(x^k, y^k\right)^T \begin{pmatrix} x - x^k \\ y - y^k \end{pmatrix} + g\left(x^k, y^k\right) \leqslant 0 \\
&\forall \left(x^k, y^k\right) \in T \\
&x^L \leqslant x \leqslant x^U; y \in Y
\end{aligned} \tag{9.9}$$

The lower bound of MINLP is updated by $z^L = \alpha$. The integer solution y^k is fixed and the resulting NLP is solved

$$\begin{aligned}
&\underset{x}{min}\, f\left(x, \widehat{y}\right) \\
&\text{s.t.} \\
&g\left(x, \widehat{y}\right) \leqslant 0 \\
&x^L \leqslant x \leqslant x^U
\end{aligned} \tag{9.10}$$

If the NLP is feasible, and if $f\left(x^k, y^k\right) < z^U$, then update $z^U = f\left(x^k, y^k\right)$. If the NLP is infeasible, the following NLP is formulated to minimize violations of constraints

$$\begin{aligned}
&\underset{x,u}{min} \sum_{j=1}^{m} u_i \\
&\text{s.t.} \\
&g\left(x, \widehat{y}\right) \leqslant u \\
&u \geqslant 0 \\
&x^L \leqslant x \leqslant x^U, u \in \Re^m
\end{aligned} \tag{9.11}$$

Solution of one of two NLPs will be added to the set of linearization points T. The outer approximation algorithm continues until $z^U - z^L \leqslant \delta$.

D Extraction of an optimization model from a simulation model in EPANET

The objective of this section is to develop a method to directly extract models from EPANET simulation models for easily and accurately formulating optimization problems, so that the expense needed for establishing the model equations can be reduced and prune-errors can be avoided. Model equations of a WDS consist of conservation laws of all components in the system. To formulate these equations, the structure of the network, the data as well as the variables of each component in the network are needed. The structure and component data of WDSs, as shown in Table 9.1, can be accessed by using the EPANET Programmer Toolkit [124]. Therefore, we develop a C program to access such information from EPANET. Based on this information, model equations for the components can be established according to their conservation laws. Struct types

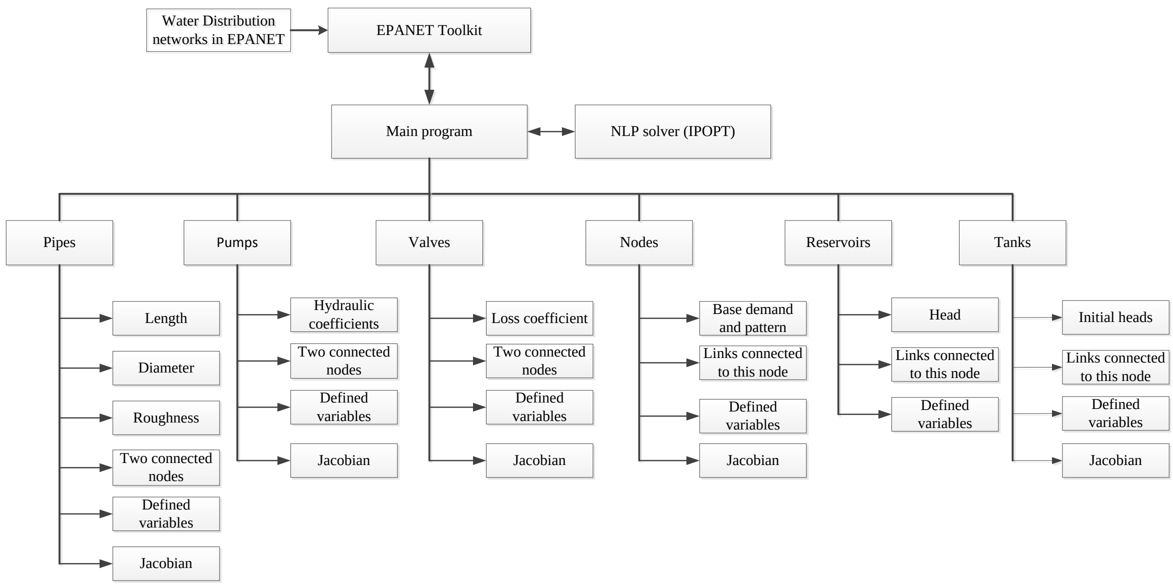


Figure 9.1: The extraction of optimization model from EPANET simulation environment

in the C programming language are used to manage data of each component in a WDS. As seen in Fig.9.1, variables necessary for formulation of the optimization problem are defined for each component (e.g., pipes,valves,pumps,nodes,tanks). As an example, 24 variables are defined for every pipe to represent their flows in 24hours.The C program is linked to a NLP solver, i.e., IPOPT [117], to solve the formulated NLP problem. In addition, the jacobian of equality/inequality constraints describing components in WDSs is calculated and supplied to the NLP solver. The objective functions can be changed according to different optimization tasks. For examples, with optimization of pressure regulation, the objective function is the sum of excessive pressures at nodes while the objective function is pumping energy costs for optimizations of pump scheduling problems. The gradient information of these objective functions is calculated and also supplied to the NLP solver.

In Table 9.1 NJ is the number of junctions (nodes); NP is the number of pipes; NT is the number of tanks; NPU is the number of pump stations; NR is the number of reservoirs; NV is the number of valves.

Table 9.1: Properties for modeling network components

Components	**Properties**	**Variables in time horizon** T.	**Number of variables**
Junctions/nodes	ID label Elevation Demand Demand pattern Pipes connected to the node	Heads	NJ×T
Reservoirs	ID label Elevation	Heads	NR×T
Tanks	ID label Bottom elevation Initial water level Pipes connected to this node Water level-volume curve	Heads	NT× (T+1)
Pipes	ID label Start node label End node label Diameter Length Roughness	Flow rates	NP×T
Pumps	ID label Start node label End node label Head-discharge curve	Flow rates. Pump speeds	NPU×T NPU×T
Valves	ID label Start node label End node label Loss coefficient	Flow rates Valve setting	NV×T NV×T

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