



**Multiobjective Genetic Algorithm Optimization
of Water Distribution Systems Accounting for
Economic Cost, Greenhouse Gas Emissions and
Reliability**

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*To my family - my mum, dad,
beloved husband and son.*

Abstract

Multiobjective optimization is becoming an increasingly important approach for both the design and operation of water distribution systems (WDSs). Given the multiobjective nature of these problems, multiobjective optimization is expected to provide decision makers with increased insight into the tradeoffs between competing objectives and alternative solutions of WDSs, which might benefit the water industry, society and environment. Due to the advances in computing technology and the development of fast multiobjective sorting algorithms, research activities into the application of multiobjective algorithms to WDS design and operation have increased significantly in the past decade. Minimization of economic cost and maximization of network reliability are the two most commonly considered objectives in WDS optimization. In addition, some environment related issues, such as energy conservation, have been incorporated into the optimization of WDSs. However, the leading environmental concern – Greenhouse gas (GHG) emissions – has not yet been addressed directly in the field of WDS optimization. Consequently, this research incorporates GHG emission minimization as an objective directly into the optimal design of WDSs, together with the economic objective of minimizing cost and the hydraulic reliability objective of maximizing surplus power factor via a multiobjective approach.

The major research contributions are presented in six journal publications. These publications describe the motivation and methodology to incorporate GHG emission minimization as an objective of WDS optimization; explore the tradeoffs between the traditional objective of minimizing life cycle cost and the environmental objective of minimizing life cycle GHG emissions; investigate the sensitivity of these tradeoffs to a number of factors, including

the discount rate, electricity tariffs and emission factors used in the objective function evaluation process, the price of carbon under a potential emissions trading scheme and the use of fixed-speed or variable-speed pumps; and finally examine the impact of the inclusion of the hydraulic reliability objective of maximizing surplus power factor on WDS optimization account for economic cost and GHG emissions.

In addition, two technical issues have also been solved in order to achieve the overall research aim. First, an optimization based generic pump power estimation method has been developed in this research to efficiently estimate the size and pump power of the pumps required for different network configurations, thus variable-speed pumps can be incorporated into the optimal design of WDSs. Secondly, a new hydraulic reliability measure based on the concept of surplus power factor has been incorporated into the optimal design of WDSs. The advantage of this hydraulic measure over currently used hydraulic reliability measures is that it can be used for WDSs involving the delivery of water into storage facilities, where other measures have failed.

The overall contribution of this research is the incorporation of GHG emission consideration into the design optimization of WDSs together with the traditional economic and reliability objectives via a multiobjective approach. It is anticipated that this research will lead to a new paradigm for the optimization of WDSs in the real world.

Statement of Originality

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Journal Publications

1. Wu, W., Simpson, A. R., and Maier, H. R. (2010). "Accounting for Greenhouse Gas Emissions in Multiobjective Genetic Algorithm Optimization of Water Distribution Systems." *Journal of Water Resources Planning and Management*, 136(2), 146-155.
2. Wu, W., Maier, H. R., and Simpson, A. R. (2010). "Single-Objective versus Multi-Objective Optimization of Water Distribution Systems Accounting for Greenhouse Gas Emissions by Carbon Pricing." *Journal of Water Resources Planning and Management*, 136(5), 555-565.
3. Wu, W., Simpson, A. R., and Maier, H. R. (2012) "Incorporation of Variable-speed Pumping in Multiobjective Genetic Algorithm Optimization of the Design of Water Transmission Systems." *Journal of Water Resources Planning and Management*, (in press).
4. Wu, W., Simpson, A. R. and Maier, H. R. (2012). "Sensitivity of Optimal Tradeoffs between Cost and Greenhouse Gas Emissions for Water Distribution Systems to Electricity Tariff and Generation." *Journal of Water Resources Planning and Management*. 138(2), 182-186.
5. Wu, W., Maier, H. R. and Simpson, A. R. (2011) "Surplus Power Factor as a Resilience Measure for Assessing Hydraulic Reliability in Water Transmission System Optimization." *Journal of Water Resources Planning and Management*. 137(6), 542-546.

6. Wu, W., Maier, H. R. and Simpson, A. R. (2012). “Multiobjective Optimization of Water Distribution System Design Accounting for Economic Cost, Greenhouse Gas Emissions and Hydraulic Reliability.” *Water Resources Research*. (submitted).

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List of Abbreviations

ABARE	Australian Bureau of Agricultural and Resource Economics
ACOA	Ant Colony Optimization Algorithms
CE	Cross-Entropy
CO ₂ -e	Carbon dioxide equivalent
DICL	Ductile iron cement mortar lined
EA	Evolutionary algorithm
FCV	Flow control valve
FORM	First Order Reliability Method
FSP	Fixed speed pump
GA	Genetic algorithm
GHG	Greenhouse gas
HMT	Her Majesty's Treasury
IPCC	Intergovernmental Panel on Climate Change
MOGA	Multi-objective Genetic Algorithm [an algorithm developed by Fonseca and Fleming (1993)]
NSGA	Non-dominated Sorting Genetic Algorithm
NYT	New York tunnel
PVA	Present value analysis
SA	Simulated Annealing
SFLA	Shuffled Frog Leaping Algorithms
SPEA	Strength Pareto Evolution Algorithm
VEGA	Vector Evaluated Genetic Algorithm
VFD	Variable frequency drive
VSP	Variable speed pump
WBGA	Weight-based Genetic Algorithm

List of Abbreviations

WDS	Water distribution system
WSMGA	Water System Multiobjective Genetic Algorithm
WTS	Water transmission system

Chapter 1

Introduction

1.1 Research background

Water distribution systems (WDSs) are an essential part of urban infrastructure systems (UISs), as urban water consumers (domestic, commercial and industrial) rely on these systems to obtain clean water to perform basic activities (Filion et al., 2004). Due to the high cost associated with the construction and maintenance of WDSs, WDS optimization has been an important research sector within the field of civil and environmental engineering for over three decades (Simpson et al., 1994; Zecchin et al., 2006). Recently, the need for WDS optimization has been emphasized, because: 1) much urban infrastructure, including WDSs, built by the late 1960s has shown signs of ageing and deterioration (Sahely et al., 2005), thus significant reinvestment is required; 2) growing awareness of wastewater reuse and associated increase in treated water quality criteria has led to an increase in the costs of providing high quality drinking water to urban areas (Hiessl et al., 2001); and 3) the increase in both the extent and density of urban areas caused by urbanization also requires upgrading of existing urban WDSs, and planning and design of new systems. The increasing need for the optimal planning, design and evaluation of WDSs is the first motivation for this research.

Climate change, especially global warming caused by human activities, presents serious global risks. Extreme weather conditions such as severe

droughts, floods and cyclones, exacerbated by global warming, are already affecting a large number of people around the world. In order to mitigate global warming, individuals, governments and industries need to be more energy efficient and reduce their greenhouse gas (GHG) emissions. Within the civil engineering domain, the minimization of GHG emissions has been identified as one important criterion for improving the sustainability of urban infrastructure and urban water systems (Sahely et al., 2005; Filion, 2008). In a number of studies in WDS research, GHG related issues, such as energy consumption, have already been addressed in both the optimization area (Sarbu and Borza, 1998; Baran et al., 2005; Lopez-Ibáñez et al., 2005; Ulanicki et al., 2007) and the planning and management area (Lundie et al., 2004; Filion, 2008). It was not until 2006 that GHG emissions were evaluated for a WDS (Dandy et al., 2006). However, in the study by Dandy et al. (2006) GHG emission minimization was not integrated into the optimization of WDSs as a design criterion. Consequently, there is a need to include GHG emission minimization as an objective directly into the optimal design of WDSs, which is the second motivation for this research.

The ultimate goal of incorporating GHG emissions into the optimal design of WDSs is to reduce these emissions from WDSs. However, in practice, there are many factors that have an impact on the selection of the final design of a WDS and thus the total amount of GHG emissions generated from the system. First of all, the discount rate used in present value analysis in the objective function evaluation process has a significant impact on the final value of objective function(s), and thus the final design of the system. Secondly, the introduction of an emissions trading scheme may lead to the pricing of carbon related emissions, which will have an impact on the formulation of the optimization of WDSs accounting for economic cost and GHG emissions. Thirdly, within the water industry, GHG emissions are mainly generated from system operation related to pumping (Kelly, 2007). As a result, the type of pump selected [e.g. fixed speed pumps (FSPs) or variable speed pumps (VSPs)] also has a significant impact on the total GHG emissions generated from a WDS. Fourthly, the electricity tariffs into the future will have a significantly impact on the operating cost, and thus the life cycle, of WDSs,

which in turn may alter the final system configuration selected. Finally, the methods used to generate electricity have a direct impact on the GHGs emitted from WDSs. As the proportion of renewable energy (i.e. wind, solar and hydroelectric energy) increases in the future, the GHG emissions from the operation of WDSs will be reduced. Consequently, the third motivation for this research is to explore the sensitivity of GHG emissions from a WDS to the factors listed above.

The optimization of WDSs has always been a multiobjective problem involving economic, environmental and reliability considerations. While reference to multiobjective WDS optimization was first made in the literature in the late 1960s (Schaake and Lai, 1969), attention has mainly been given to the minimization of the economic cost of the networks alone (Woodburn et al., 1987; Lohani and Fontane, 1988; Su and Mays, 1988; Walski et al., 1988; Lansey et al., 1989; Simpson et al., 1994; Loganathan et al., 1995; Vairavamorthy and Ali, 2000; Perelman and Ostfeld, 2005). Other considerations, such as system reliability, are often taken into account as optimization constraints, rather than objectives (Duan et al., 1990). It was not until late the 1990s that multiobjective optimization techniques were applied to WDS optimization to account for more than one objective (Halhal et al., 1997; Ilich and Simonovic, 1998).

During the past 10 years, as computing technologies and multiobjective optimization algorithms have become more efficient, research activities in the field of multiobjective optimization of WDSs have increased significantly. Many studies have been carried out to include objectives other than the traditional economic objective of minimizing cost into the optimization of WDSs via a multiobjective approach (Dandy and Hewitson, 2000; Wegley et al., 2000; Dandy and Engelhardt, 2006; Rao and Salomons, 2007; da Costa Bortoni et al., 2008; Wu et al., 2009). Among the current multiobjective WDS optimization studies, hydraulic reliability is one objective that has been considered most often due to its importance in ensuring the maintenance of services to end water users (Savic, 2002; Keedwell and Khu, 2004; Jourdan et al., 2005; Atiquzzaman et al., 2006; Jayaram and Srinivasan, 2008). However,

the leading environmental concern – GHG emission minimization – has not been addressed directly in the field of multiobjective WDS optimization. Consequently, the fourth motivation for this research is to incorporate multiple design objectives, including the minimization of life cycle cost and GHG emissions, and the maximization of hydraulic reliability, into the optimization of WDSs simultaneously via a multiobjective approach.

There are several issues that need to be addressed in order to carry out this research. First of all, in order to explore the impact of the use of a FSP or a VSP on multiobjective WDS optimization accounting for GHG emissions, the required pump size and associated pump power for each different network configuration evaluated in the optimization process need to be estimated. This requires the development of an approach to pump sizing and pump power estimation, which allows easy adjustment of pump power based on specific network configurations assessed in an optimization process, thereby enabling both FSPs and VSPs to be incorporated into the design optimization of WDSs.

Secondly, the hydraulic reliability measures used in current literature often cannot be used for systems involving the pumping of water into reservoirs or storage tanks, which generate significant amount of GHG emissions. This is because the calculation of the hydraulic reliability measures employed in current literature relies on the difference between the required and minimum allowed pressure heads at the outlet of the system, which is zero for systems delivering water into storage facilities. Consequently, there is a need to find a suitable hydraulic reliability measure for such WDSs.

The last issue is to select a suitable technique for solving the multiobjective WDS optimization problem proposed in this research. In the literature, many approaches have been used to optimize WDSs. These approaches include enumeration (Savic and Walters, 1997), mathematical programming techniques, such as linear programming (Shamir, 1974) and non-linear programming (Gupta et al., 1999), and evolutionary algorithms (EAs), such as genetic algorithms (GAs) (Simpson et al., 1994) and ant colony optimization (Zecchin et al., 2007). Enumeration becomes infeasible when applied to the

optimization of any realistic-sized WDS (Savic and Walters, 1997). Traditional mathematical programming techniques often converge to local optima when applied to complex non-linear optimization problems, such as WDS optimization (Calgari et al., 1999) and many of them are not suitable for solving multiobjective optimization problems (Coello Coello, 2005). In contrast, EAs have been found to be effective for WDS optimization problems (Simpson et al., 1994; Eusuff and Lansey, 2003; Zecchin et al., 2007). Particularly, multiobjective GAs have been used successfully in WDS optimization research (Savic, 2002; Farmani et al., 2005; Keedwell and Khu, 2006; Jayaram and Srinivasan, 2008). Consequently, a multiobjective GA is used in this research to incorporate the economic, environmental and reliability objectives into the optimal design of WDSs.

1.2 Research aims

The overall aim of this study is to incorporate the minimization of the leading environmental concern - GHG emissions - as an objective into the optimal design of WDSs via a multiobjective approach, together with the traditional objectives of minimizing life cycle economic cost and maximizing hydraulic reliability of WDSs. Ultimately, it is hoped that this will lead to the consideration of environmental objectives and the adoption of a multiobjective framework for the design of WDSs in real world practice. In order to fulfill the overall aim of this research, ten research aims have been developed and listed below. How these ten research aims are related to each other is illustrated in Figure 1.1.

Aim 1: To develop a framework for incorporating the environmental objective of the minimization of life cycle GHG emissions into the optimization of WDSs via a multiobjective approach.

Aim 2: To investigate the tradeoffs between the economic objective of minimizing the life cycle cost and the environmental objective of minimizing

the life cycle GHG emissions of WDSs via a multiobjective optimization approach.

Aim 3: To investigate the sensitivity of the tradeoffs between the economic objective of minimizing life cycle cost and the environmental objective of minimizing life cycle GHG emissions to the selection of the discount rate in the present value analysis for objective function evaluation.

Aim 4: To investigate the potential impact of a carbon price under an emissions trading scheme on multiobjective optimization of WDSs accounting for both the economic and environmental objectives.

Aim 5: To develop a generic pump power estimation method that can be used to efficiently estimate the size and pump power of the pumps (particularly VSPs) required for different network configurations evaluated in an optimization process.

Aim 6: To investigate the potential impact of the type of pumps (i.e. fixed-speed or variable-speed) selected on both the economic cost and GHG emissions of WDSs.

Aim 7: To investigate the sensitivity of the tradeoffs between the economic objective of minimizing life cycle cost and the environmental objective of minimizing life cycle GHG emissions to electricity tariffs and generation.

Aim 8: To find a suitable hydraulic reliability measure for WDSs involving pumping water into storage facilities, which are often the primary cause of GHG emissions.

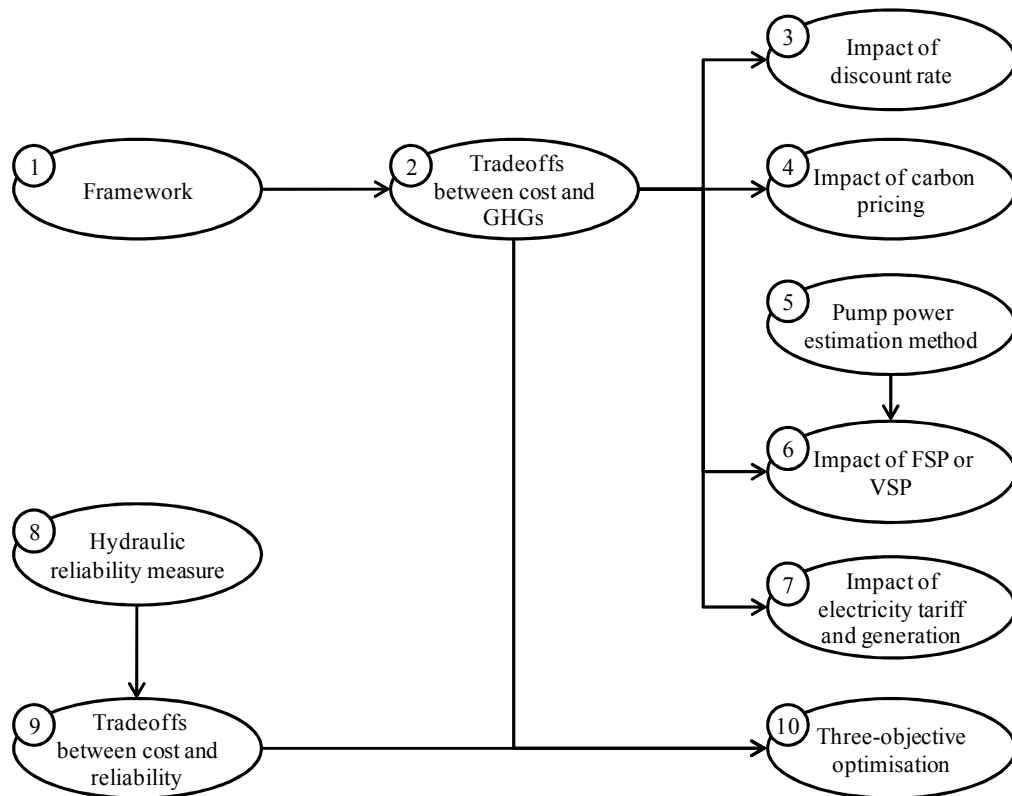


Figure 1.1 Ten research aims and their hierarchy

Aim 9: To investigate the tradeoffs between the objective of minimizing life cycle economic cost and the objective of maximizing hydraulic reliability of WDS optimization via a multiobjective approach.

Aim 10: To investigate the impact of the inclusion of hydraulic reliability maximization as a design objective on multiobjective WDS optimization accounting for the economic objective of minimizing life cycle cost and environmental objective of minimizing GHG emissions and to explore the interaction of the three objectives in a three dimensional objective space.

As can be seen from Figure 1.1, the first seven research aims are all concerned with the multiobjective optimization of WDSs accounting for the economic objective of minimizing life cycle cost and the environmental objective of minimizing life cycle GHG emissions. The first aim is to develop a

framework to evaluate the life cycle GHG emissions of WDSs and incorporate them into the optimization of WDSs via a multiobjective approach. The second aim is to investigate the tradeoffs between the economic and environmental objectives using a number of case studies; thus, questions such as how much GHG emission reduction can be achieved at what cost can be answered. Research aims 3, 4, 6 and 7 are to explore the impact of different factors on multiobjective WDS optimization accounting for economic cost and GHG emissions. These factors include the discount rate (Aim 3), the pricing of carbon related emissions under an emissions trading scheme (Aim 4), the use of a FSP or a VSP (Aim 6) and the future electricity tariffs and generation methods (Aim 7). In order to achieve aim 6, a generic pump power estimation method that can be used to estimate the required size and pump power for each network configuration evaluated in an optimization process needs to be developed (Aim 5). The eighth aim is to find a suitable hydraulic reliability measure for WDSs involving pumping water into storage facilities, based on which the tradeoffs between the objective of minimizing life cycle economic cost and the objective of maximizing hydraulic reliability of WDSs can be explored (Aim 9). The final aim of this research (Aim 10) is to investigate the impact of the inclusion of hydraulic reliability maximization as a design objective on multiobjective WDS optimization accounting for the economic objective of minimizing life cycle cost and environmental objective of minimizing GHG emissions and to explore the interaction of the three objectives in a three dimensional objective space.

1.3 Organization of thesis

This thesis is presented as a collection of journal publications arising from the research undertaken and is divided into 11 chapters. **Chapters 2 and 3** provide comprehensive reviews of literature on the background of this research, including WDS optimization and the multiobjective genetic algorithms which are used in this research, while **Chapter 4** provides a synopsis of the publications that form the main body of this thesis. The

synopsis provides a summary of each journal publication and illustrates their contributions to this research by describing how each publication is linked to the ten aims of this research listed in the previous section.

The main body of this thesis consists of Chapters 5 to 10, which are formed by the six journal publications produced for this research. Chapters 5 to 8 are concerned with the tradeoffs between the economic objective of minimizing life cycle cost and the environmental objective of minimizing life cycle GHG emissions of WDSs. **Chapter 5** presents the framework to incorporate the life cycle GHG emissions of WDSs into the optimization of WDS via a multiobjective approach (Aim 1). In Chapter 5, the tradeoffs between the economic and environmental objectives of WDSs and the sensitivity of the tradeoffs to the discount rate used in objective function evaluation are also investigated (Aims 2 and 3). **Chapter 6** answers the question of whether or not a multiobjective approach of WDS optimization accounting for economic cost and GHG emissions becomes obsolete under an emissions trading scheme where GHG emissions will be priced (Aim 4). **Chapter 7** explores the impact of the selection of fixed speed pumps (FSPs) or variable speed pumps (VSPs) on the multiobjective WDS optimization accounting for economic cost and GHG emissions and demonstrates that by switching from FSPs to VSPs in WDS design optimization, both life cycle cost and GHG emissions can be reduced (Aim 6). In order to achieve aim 6, a technical issue of incorporating variable speed pumping into the design optimization of WDSs is also solved in Chapter 7 (Aim 5). **Chapter 8** explores the impact of electricity tariffs and generation on the tradeoffs between the economic and environmental objectives via a sensitivity study (Aim 7). **Chapter 9** is concerned with research aims 8 and 9. It first introduces the concept of the surplus power factor developed by Vaabel et al (2006) as a hydraulic reliability measure for WDSs involving pumping water into storage facilities and demonstrates the applicability of this hydraulic reliability measure using a number of benchmark case studies (Aim 8). It then explores the tradeoffs between the economic cost and hydraulic reliability of WDSs represented using the surplus power factor (Aim 9). **Chapter 10** investigates the impact of the inclusion of the hydraulic reliability objective on the tradeoffs between the economic

objective of minimizing life cycle cost and the environmental objective of minimizing GHG emissions (Aim 10). In this chapter, the interaction of the three WDS design objectives in a three dimensional objective space is also explored (Aim 10).

The final chapter, **Chapter 11**, summarizes the major contributions of this research. In addition, the publications produced and the limitations and future directions of this research are also summarized.

Chapter 2

Water Distribution System Optimization

2.1 Water distribution systems

Water distribution systems (WDSs) are part of urban infrastructure systems. The system boundaries of a WDS are illustrated in Figure 2.1. In general, WDSs consist of a collection of water storage facilities, such as reservoirs and tanks, and water distribution facilities, such as pumps, pipes, valves, etc. These network components need to be arranged in a complex way, such that sufficient water is first delivered to storage facilities through transmission mains and then to end water users with adequate pressure through distribution mains. Due to the large scale of WDSs and the complexity of the arrangement of their components, optimization techniques are often required to design WDSs.

2.2 WDS optimization problems

2.2.1 Problem formulation

A WDS optimization problem can take many forms. Most WDS optimization problems generally fall into one of three categories: 1) the design of a new

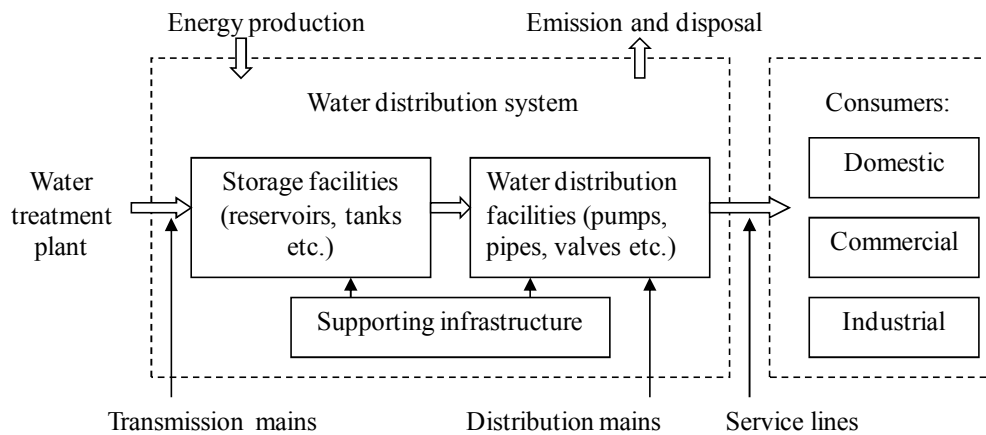


Figure 2.1 System boundaries of a water distribution system

system/subsystem, 2) the rehabilitation of an existing system, and 3) the optimal operation of a system. A new design problem typically involves selecting the diameter of pipes, when the locations of all pipes are given (Zecchin et al., 2005). Quite often, other system components, such as pumps, tanks and valves also need to be considered (Duan et al., 1990). A rehabilitation problem refers to improving the performance of an existing network by cleaning, replacing, duplicating or repairing network components, typically pipes (Halhal et al., 1997). A system operation problem typically refers to finding optimal operational strategies, such as suitable pump trigger levels or pump scheduling (McCormick and Powell, 2004; Lopez-Ibáñez et al., 2005).

No matter which category it falls into, a WDS optimization problem can be defined as selecting the best combination of the values for decision variables in terms of certain objectives for the design, rehabilitation or operation of a WDS such that a number of constraints are satisfied. Thus, a WDS optimization problem can be expressed using the following equations:

$$\text{Minimize/maximize} \quad OF_i = f(\vec{x}) \quad i = 1, 2, \dots, m \quad (2.1)$$

subject to

$$GF_j \geq 0 \quad j = 1, 2, \dots, p \quad (2.2)$$

$$HF_k = 0 \quad k = 1, 2, \dots, q \quad (2.3)$$

and

$$LB_t \leq x_t \leq UB_t \quad t = 1, 2, \dots, n \quad (2.4)$$

where OF = objective functions; x = decision variables; n = the number of decision variables; m = the number of objectives; GF = inequality constraint functions; p = the number of inequality constraints; HF = equality constraint functions; q = the number of equality constraints; LB_t and UB_t are the lower bound and upper bound of the t th decision variable, respectively. In this thesis, different combinations of the values of decision variables are also referred to as trial solutions or potential solutions. A decision variable is defined as a factor whose value is subject to change within a problem and will affect values of the objective functions and constraints. The combination of decision variables make up the solution to the problem being addressed.

Decision variables of a WDS design optimization problem often involve the sizes of pipes, sizes and shapes of tanks, capacity and type of pumps, valves and their locations (Zecchin et al., 2006). Selecting the right pipe size is the most common application for WDS optimal design problems (Walski et al., 1988; Varma et al., 1997; Abebe and Solomatine, 1998; Vairavamoorthy and Ali, 2000; Babayan et al., 2005). For a WDS rehabilitation problem, decision variables also involve pipes. Typically, decisions regarding which pipe to rehabilitate (Walski et al., 1987), what rehabilitation method to use (Simpson et al., 1994) and the optimal rehabilitation timeline need to be made. For WDS operation problems, decision variables may include selection of trigger levels in tanks and pump scheduling (Lopez-Ibáñez et al., 2005; Ulanicki et al., 2007). The decision variables of WDS optimization, such as pipe sizes and

on and off of pumps, often take discrete values, thus Equation 2.4 can be expressed as:

$$x_t \in \{x_{t1}, x_{t2}, \dots, x_{tl}\} \quad (2.5)$$

where, $\{x_{t1}, x_{t2}, \dots, x_{tl}\}$ are the l discrete values of the t th decision variable. As a result, the search space of these WDS optimization problems is also discrete.

The constraints of WDS optimization problems mainly include hydraulic constraints and available options of decision variables. Hydraulic constraints refer to the physical rules that a hydraulic system must obey, which include:

1. Conservation of mass: The continuity of flow must be maintained at each node in the network;
2. Conservation of energy: The total head loss around a loop must be zero and the total head loss around a path must equal the difference between the heads of the two end reservoirs.

The available options of decision variables often involve commercially available diameters of pipes, and sizes and types of pumps.

In addition to the general constraints discussed above, different case-specific constraints may apply to different optimization problems. Maximum allowable velocity in each pipe and minimum and maximum allowable pressures at demand nodes are common case-specific constraints for WDS optimization problems (Varma et al., 1997; Abebe and Solomatine, 1998; Samani and Mottaghi, 2006). In Pezeshk and Helweg's (1996) study on WDS operation problems, minimum and maximum allowable pressure are set to trigger a pump. In Dandy and Hewitson's (2000) research on water quality optimization, acceptable limits of chlorine levels need to be satisfied. Water quality was also used as a constraint in a study conducted by Broad et al. (2005).

In addition, as can be seen from the equations above, the WDS optimization problem is essentially a multiobjective optimization problem. Seeking the

least cost network configuration has always been the focus of WDS optimization due to the high cost associated with the construction, maintenance and operation of these systems (Walski et al., 1987; Simpson et al., 1994; Boulos et al., 2001; Bounds et al., 2006). Network reliability is another traditional research focus for WDS optimization, as it is important to ensure the service provided by the system is maintained. In recent years, due to the increased awareness of sustainability, environmental and health related issues, such as energy consumption (Ulanicki et al., 2007), water quality (Dandy and Hewitson, 2000) and environmental impact (Herstein et al., 2009b) have also been incorporated into WDS optimization. An overview of multiobjective optimization problems and a review of different objectives used in WDS optimization are presented in the following two subsections.

2.2.2 Multiobjective optimization problem overview

A multiobjective optimization problem uses the concept of domination introduced by Fonseca and Fleming (1993) to deal with the tradeoffs between or among conflicting objectives (Deb, 2002). A solution x is said to dominate a solution y , if both of the following conditions are true:

1. Solution x is no worse than solution y in all objectives;
2. Solution x is strictly better than solution y in at least one objective.

An example of the tradeoffs between two conflicting objectives of a minimization problem is shown in Figure 2.2. Each black dot in the figure represents a solution point in the objective space. It can be seen that Solution B is better than Solution A in terms of objective 1, but that they both have the same value for objective 2. As a result, Solution B is said to dominate Solution A. Comparing Solutions B and C, B is better in terms of objective 1 but worse in terms of objective 2. Therefore, Solutions B and C are called non-dominated solutions. The solutions within the solid circles dominate all other solutions in the objective space. However, they are non-dominated solutions to each other. These non-dominated solutions are called Pareto-

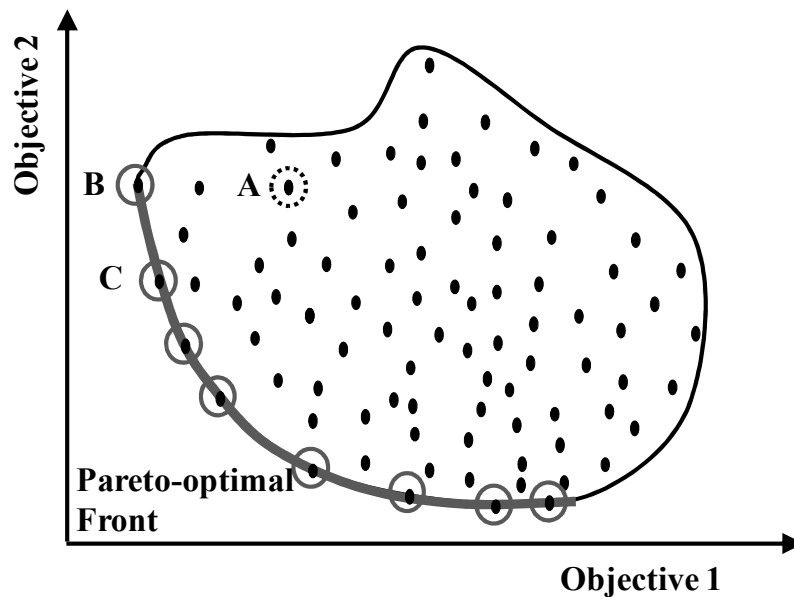


Figure 2.2 Objective space and Pareto-optimal front of a two-objective minimization problem

optimal solutions. They form a front (the darker line), referred to as the Pareto-optimal front.

If there is higher level information available for decision making, a biased search can be used to find desired solutions among the Pareto-optimal solutions. However, in most cases such information is not available. Therefore, the Pareto-optimal solutions are equally important. The ultimate goal of multiobjective optimization is to find all of these Pareto-optimal solutions. However, multiobjective optimization problems are complex and non-linear. Consequently, it is often impossible to find all Pareto-optimal solutions within the desired/available computational time using current technologies. Seen in this way, there are two goals in multiobjective optimization (Deb, 2002):

1. To find a set of non-dominated solutions as close to the Pareto-optimal front as possible;

2. To find a set of non-dominated solutions as diverse within the optimality region as possible.

The quality of a multiobjective algorithm can be judged by using these two goals.

2.2.3 WDS optimization objectives

In traditional WDS optimization practices, finding the least expensive network has always been the objective of WDS optimization due to the high cost associated with the construction of these systems (Zecchin et al., 2006). Many early WDS optimization studies are dedicated to this subject in the literature (Schaake and Lai, 1969; Alperovits and Shamir, 1977; Simpson et al., 1994; Abebe and Solomatine, 1998; Vairavamoorthy and Ali, 2000; Lopez-Giraldo and Saldarriaga, 2004; Babayan et al., 2005; Reca et al., 2008). WDSs, also have long service lives (e.g. 100 years or longer for water mains) (Park et al., 1998; Water Services Association of Australia, 2002) and therefore, the maintenance and operation costs of WDSs have also been considered in previous studies. In a network optimization problem described by Walski et al. (1987), the cost function includes the capital cost, network maintenance cost and energy cost. Minimizing operational cost is also a typical objective in WDS operational optimization problems (Boulos et al., 2001; Bounds et al., 2006).

Network reliability is also a traditional research focus for WDS optimization, as it is important to ensure the service of the system is maintained. Network reliability includes mechanical reliability and hydraulic reliability (Mays et al., 1989; Schneiter et al., 1996). Mechanical reliability refers to 1) network “connectability”, which is defined as the probability of a given demand node connected to a water source and 2) network “reachability”, which refers to the probability of all demand nodes in a network connected to a water source (Wagner et al., 1988). Hydraulic reliability addresses issues related to the probability of a WDS satisfying end water users or the probability of a network delivering sufficient flows at required pressures at each demand node

(Wagner et al., 1988; Schneider et al., 1996). During early research, attention was mainly given to mechanical reliability and hydraulic reliability received less attention than it deserved (Wagner et al., 1988; Li et al., 1993). However, hydraulic reliability is the ultimate goal of WDS design, as it refers directly to the basic function of a WDS (Ostfeld et al., 2002).

There are no universally accepted network reliability measures and many methods have been developed to measure the hydraulic reliability of WDSs (Mays, 1996; Todini, 2000). As early as 1985, Gessler and Walski (1985) used the excess pressure at the worst node in the system as a benefit measure in a pipe network optimization problem to ensure sufficient water with acceptable pressure is delivered to demand nodes. In 1993, Li et al. (1993) extended the network reliability analysis to include capacity reliability, which is defined as the probability that the carrying capacity of a network meets the demand. Schneider et al. (1996) applied the concept of capacity reliability to a WDS optimal rehabilitation problem.

The multiobjective optimization of WDSs accounting for network reliability was first investigated by Halhal et al. (1997). In their study, the authors minimized the network cost and maximized the total benefit (the sum of hydraulic benefit, physical integrity benefit, flexibility benefit and quality benefit) of the network. In the benefit function, the hydraulic benefit is defined as the improvement in the pressure deficiencies in the network. Since then, minimizing the head deficit at demand nodes has been used as a hydraulic capacity reliability measure in many multiobjective WDS optimization studies considering both cost and system reliability (Savic, 2002; Keedwell and Khu, 2004; Jourdan et al., 2005; Atiquzzaman et al., 2006).

In 2000, Todini (2000) introduced the concept of resilience as one measure of network capacity reliability. In his study, Todini defined resilience as the capacity of the network to react and overcome failure or stress of the system. Network resilience can be measured using a resilience index (I_r), which is the quotient of the difference between the actual output power and the required output power and the difference between the total input power and

the required output power. The higher the resilience index, the more redundant energy a network will have to overcome stress conditions, thereby, the capacity reliability is increased. Based on the concept of resilience, Prasad and Park (2004) introduced a new resilience measure called network resilience. In calculating network resilience, the effects of both surplus power and reliable loops are considered. A loop is considered to be reliable if the pipes connected to each node in the loop are not very different in terms of diameter.

Around the same time as Prasad and Park's work, researchers started looking at the uncertainties involved in network reliability evaluation. Tolson et al. (2001) used the First Order Reliability Method (FORM) to estimate water distribution system reliability. Thereafter, Tolson et al. (2004) used a genetic algorithm coupled with FORM to obtain optimal tradeoffs between the cost and reliability of WDSs represented by the probability of failure. Kapelan et al. (2005) used a multiobjective approach to maximize the robustness of a WDS, which was represented as the possibility that pressure heads at all network nodes are simultaneously equal to or above the minimum required pressure. Recently, Jayaram and Srinivasan (2008) introduced a modified resilience index, which is developed based on the resilience index of Todini (2000). In calculating the modified resilience index, the authors replaced the denominator of the resilience index by the required power at the demand nodes. Thus, the modified resilience index can be used to compare the resilience of different networks (Jayaram and Srinivasan, 2008).

Since 1987, when the concept of sustainability was brought to international attention through the Brundtland Report (World Commission on Environmental and Development, 1987), there has been an increasing awareness of the environmental impacts from human activities, which has led to the incorporation of environmental objectives in WDS optimization. The minimization of energy consumption due to pumping-related WDS operation is the most commonly considered environmental objective for WDS optimization. Pumping is a major contributor to energy consumption within the water industry (Ghimire and Barkdoll, 2007; Kelly, 2007) and for most

countries, electricity is generated from non-renewable sources, such as fossil fuels. Thus, WDSs pose huge burdens on the environment through energy consumption. Many studies have been dedicated to the minimization of energy consumption/cost of WDSs. A review of earlier studies was carried out by Ormsbee and Lansey (1994). More recently, Pezeshk and Helweg (1996) developed an adaptive search algorithm for minimizing pumping cost by finding the best combination of pumps that are switched on. Other operation energy minimization studies include Nitivattananon et al. (1996), Ilich and Simonovic (1998), van Zyl et al. (2004) and Ulanicki et al. (2007).

Material usage due to manufacturing network components, such as pipes, also has an impact on the environment. Firstly, it results in natural resource depletion. Secondly, the material production process also degrades the environment by generating pollutants and consuming energy generated by burning fossil fuels. Dandy et al. (2006) suggested that material usage can be used as one sustainability objective of WDS design. In their study, the total mass of pipes was suggested to be used in the objective function evaluation process, if the same material was used for all pipes; otherwise, the total energy used to manufacture the pipes, called embodied energy (Treloar, 1994), could be used instead. In subsequent research conducted by Dandy et al. (2008), the minimization of embodied energy of the pipes was incorporated into the optimization of WDSs as a sustainability objective, together with the traditional economic objective of minimizing the total cost of the network. In addition, water quality has been included in WDS optimization as part of the social cost objective (Dandy and Hewitson, 2000). More recently, Herstein et al. (2009b) proposed a multiobjective framework to incorporate environmental impact into the design of WDSs. The environmental impact of WDSs is represented using the environmental impact index, which is a single parameter that consists of measures of resource consumption, environmental discharges and environmental impacts (Herstein et al., 2009a).

2.3 WDS optimization methods

2.3.1 Early methods

WDS optimization problems are non-linear, constrained mathematical problems and are included in the class of complex combinatorial optimization problems commonly referred to as NP-hard (Parker R.D. and Edition published by Academic Press, 1988). Ideally, this type of problem can be solved by full enumeration, in which every possible combination of decision variables is simulated and evaluated. However, the search space of WDS optimization problems normally is extraordinarily large. For example, for a WDS design problem with ten decision variables and eight choices for each of these, there are 8^{10} (1,073,741,824) potential solutions in the search space. Therefore, full enumeration is often infeasible for WDS optimization problems due to the enormous computational time required to simulate every single potential solution in the search space.

Prior to the use of formal optimization methods, a simulation model based trial-and-error approach was often used for the design of WDSs (Savic and Walters, 1997). However, this method is highly variable and depends heavily on the experience of the designer. A selective enumeration method was proposed by Gessler (1985) in order to reduce the number of solutions that need to be simulated and evaluated in full enumeration. In the selective enumeration method, a heuristic approach was used to eliminate inferior solutions before they were simulated. However, such an approach requires a considerable computational time for large networks and it also results in the potential loss of the optimal solution in the pruned search space (Simpson et al., 1994). Therefore, advanced optimization techniques are required to obtain the desired solution(s) of WDS optimization problems within a feasible time.

2.3.2 Mathematical programming methods

Many mathematical programming techniques have been developed to solve WDS optimization problems over the past four decades. In 1977, Alperovits and Shamir (1977) proposed a linear programming gradient method for the design of WDS systems. This method consists of two stages. In the first stage, the system is solved for a given flow distribution using linear programming. Then, a search is conducted in the flow variable space towards the direction of minimizing the objective function value (a minimization problem is assumed). Since then, the linear programming gradient method has been adapted and improved by many researchers (Solanki and Ghosh, 1983; Fujiwara et al., 1987; Kessler and Shamir, 1989).

A number of non-linear models were developed to account for the non-linear nature of WDS optimization problems. Lansey and Mays (1989) developed a non-linear programming technique called the generalized reduced gradient method for the optimization of WDSs. Toint and Tuytens (1990) proposed a new quasi-Newton algorithm for WDS optimization and compared it to three other non-linear methods. For a comprehensive review of non-linear programming methods applied to WDS optimization problems up to 1994, readers are referred to Simpson et al. (1994). Varma et al (1997) suggested a successive quadratic programming method for WDS optimization, in which the gradient of the objective function value was obtained analytically.

Dynamic programming was also used in WDS optimization. As early as in the 1960s, Schaake and Lai (1969) used dynamic programming to search for the global optimum for a WDS design problem. Zessler and Shamir (1989) applied an iterative dynamic programming method called progressive optimality to a WDS optimal operation problem. Ertin et al. (2001) developed a framework for using dynamic programming for optimizing pump scheduling problems.

Most mathematical programming techniques have been used to solve single-objective optimization problems. When dealing with multiobjective optimization problems, whose interest mainly lies in finding multiple Pareto-optimal solutions, mathematical programming techniques have been shown to have limitations (Deb, 2002; Coello Coello, 2005):

1. For most traditional mathematical programming techniques, only one Pareto-optimal solution can be expected from one simulation run.
2. For many mathematical programming techniques, the ability to find Pareto optimal solutions is a function of the shape of the Pareto-optimal front, as not all Pareto-optimal solutions can be found for non-convex multiobjective.
3. All mathematical programming techniques require some *a priori* problem knowledge.
4. Due to limitation no. 3, mathematical programming techniques are hard to adapt to changes to the optimization problem.

In addition, most mathematical programming techniques require that the objective functions and constraints are differentiable. Therefore, it is not easy to apply such techniques to WDS optimization problems, whose search spaces are discrete.

In contrast, stochastic optimization methods, such as evolutionary algorithms (EAs), can overcome the above limitations when dealing with multiobjective combinatorial optimization problems. EAs have been applied to WDS optimization problems with great success. A review of the application of EAs to WDS optimization problems is provided in the following section.

2.3.3 Evolutionary algorithms

Evolutionary algorithms (EAs) are stochastic search methods, which belong to a class of metaheuristics. Metaheuristics are a higher level of heuristics, in which the search is guided by problem-specific knowledge in the form of heuristics (Blum and Roli, 2003). Metaheuristics have been widely used in

WDS optimization problems. Apart from EAs, other metaheuristics that have been successfully applied to WDS optimization problems include Simulated Annealing (SA) (Cunha and Sousa, 1999), Ant Colony Optimization Algorithms (ACO) (Maier et al., 2003; Zecchin et al., 2006), Shuffled Frog Leaping Algorithms (SFLA) (Eusuff and Lansey, 2003), Cross-Entropy (CE) (Perelman and Ostfeld, 2005) and Particle Swarm Optimization Algorithms (Bansal and Deep, 2009).

EAs have significant advantages when applied to combinatorial optimization problems, such as WDS optimization: 1) they can deal with discrete decision variables directly; 2) they use objective function values directly instead of auxiliary information derived from objective functions; 3) they are global search methods, which can explore a extensive areas of the search space; 4) they deal with a population of solutions simultaneously, therefore, they can be applied to multiobjective optimization problems with little modification (Coello Coello, 2005). Due to these reasons, EAs are the most widely used metaheuristics in multiobjective WDS optimization.

The multiobjective nature of WDS optimization problems was recognized in the 1960s (Schacke and Lai, 1969). While in the literature the application of multiobjective EAs to WDS optimization problems can only be traced back to the 1990s. In 1997, Halhal et al. (1997) used a structured messy GA to solve a multiobjective WDS optimization problem considering cost and benefit. In this research, the concepts of Pareto ranking (Goldberg, 1989) and fitness sharing (Goldberg and Richardson, 1987) were used, which introduced additional parameters in the optimization process. Later, the Multi-objective Genetic Algorithm (MOGA) developed by Fonseca and Fleming (1993) was employed by Savic (2002) and Dandy and Engelhardt (2006). More recently, Dandy et al. (2008) applied both the MOGA and the Non-dominated Sorting Genetic Algorithm (NSGA) developed by Srivinas and Deb (1994) to a two reservoir WDS. However, both MOGA and NSGA have been criticized for a number of drawbacks in multiobjective optimization, including high computational complexity of non-dominated sorting, lack of elitism and the need for additional parameters (Deb, 2002; Coello Coello, 2005).

In 1999, an elitist EA called Strength Pareto Evolution Algorithm (SPEA) was introduced (Zitzler and Thiele, 1999). This algorithm was improved later and named SPEA2 (Zitzler et al., 2002). SPEA2 was applied to a multiobjective pump scheduling problem and satisfactory results were obtained (Lopez-Ibáñez et al., 2005). In 2002, Deb et al. (2002) introduced another multiobjective evolutionary algorithm called Non-dominated Sorting Genetic Algorithm-II (NSGA-II), which overcame many of the drawbacks associated with NSGA. Since its introduction, NSGA-II has been successfully applied to many multiobjective WDS optimization problems (Jourdan et al., 2005; Kapelan et al., 2005; Khu and Keedwell, 2005; Atiquzzaman et al., 2006; Keedwell and Khu, 2006; Herstein et al., 2009b).

The performance of SPEA2 and NSGA-II has been compared in a number of studies. However, there is no conclusive finding on the relative performance of SPEA2 and NSGA-II. In a study conducted by Farmani et al. (2005), these two algorithms were compared based on the extent to which the multiobjective methods produced Pareto-optimal solutions and the diversity among the solutions for a number of WDS optimization problems. The authors found that both algorithms are able to identify the tradeoffs between conflicting objectives and SPEA2 performs slightly better than NSGA-II for a fixed number of generations. However, in a number of other studies (Zitzler et al., 2002; Hiroyasu et al., 2005), NSGA-II has been found to behave very similarly to SPEA2 and sometimes out-perform SPEA2 (Raisanen and Whitaker, 2005).

2.3.4 Summary of WDS optimization methods

Compared to traditional optimization techniques, EAs have significant advantages in solving multiobjective combinatorial optimization problems, such as WDS optimization problems. SPEA2 and NSGA-II are currently the most popular evolutionary algorithms applied to multiobjective WDS optimization in the literature and both algorithms are able to find near-optimal

solutions within the desired time. The performance of these two algorithms is very similar on some problems (Zitzler et al., 2002). However, as a GA, NSGA-II has a longer development history and has a wider application in multiobjective WDS optimization research. Therefore, a multiobjective GA called Water System Multiobjective Genetic Algorithm (WSMGA) has been developed based on NSGA-II in this research to solve the proposed multiobjective WDS optimization problem. In addition, an archive strategy used in SPEA2 is also adopted in WSMGA in order to improve the performance the algorithm. An overview of multiobjective GAs and the WSMGA is provided in the next chapter.

Chapter 3

Multiobjective genetic algorithms

3.1 Overview of genetic algorithms

Genetic algorithms (GAs) are a global optimization method developed by John Holland and his students at the University of Michigan (Goldberg, 1989). As the name suggests, the concept of GAs is inspired by the natural phenomenon of heredity, in which the principle of “survival of the fittest” is used to select more suitable trial solutions. In each generation of a GA, a population of alternative solutions, each represented by a vector of decision variables called a chromosome or string, is evaluated and selected based on the objectives of the optimization problem and varied (e.g. crossover and mutation) to create offspring. This process is repeated and it is expected that after some generations, the GA will produce offspring that are superior to their parent counterparts.

The general framework of a GA is shown in Figure 3.1. A GA first requires a genetic representation of the solution domain (chromosomes or strings) and a mathematical representation of the objective domain (objective functions). An encoding scheme is required to link the genetic representation of each string in a GA to its corresponding physical solution in the real world, which enables the objective functions of the string to be evaluated. A GA relies on three genetic operators – selection, crossover (or mating) and mutation – to produce offspring. The objective function value is used directly in the selection

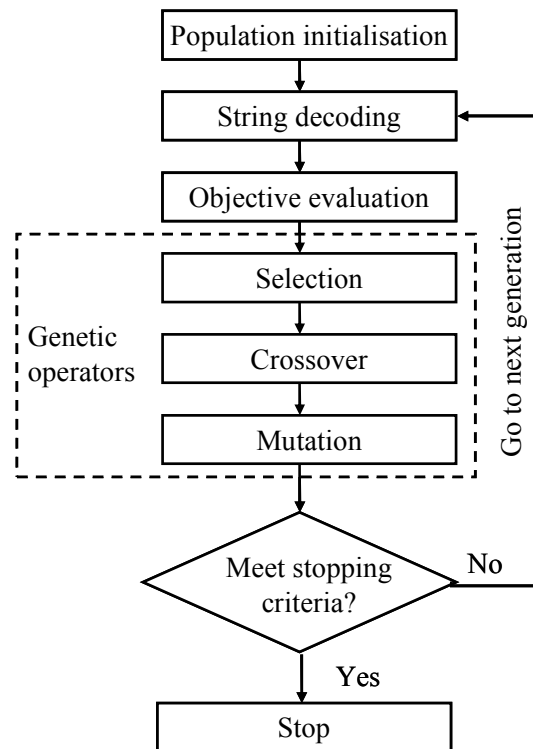


Figure 3.1 Framework of a typical GA

process as an indicator of the quality of the string and to decide whether or not a string will participate in the mating process (crossover). Once a string is selected into the mating pool, it will be paired up with another selected string and parts of each string will be exchanged (or crossed over) to produce child solutions. Mutation of each individual offspring may then occur to introduce diversity and prevent premature convergence to local optima, which is defined as the best solution(s) in a small local region of the search space. By applying the three genetic operators repeatedly, GAs maintain good solutions in the current generation and explore the searching space for better solutions in the next generation. This searching process will stop when certain stopping criteria are met. The details of these optimization steps are presented in the following sections.

3.1.1 String encoding and decoding

In traditional GAs, solutions are represented in binary as strings of 0s and 1s (Goldberg, 1989). The main advantage of this binary representation of strings is that it is strongly linked to the schema theory and building block hypothesis, which are the first attempts to explain how a GA finds the optimum by positing that near optimal solutions were forged from small, low-order, fitter-than-average schemata (Deb, 2002).

A number of difficulties arise when applying binary-coded GAs to real world problems. First of all, redundancy may occur when the number of choices for each decision variable is not a power of two, which increases the search space unnecessarily. Secondly, a binary-coded GA cannot achieve any arbitrary precision in the optimal solution in a continuous search space. The number of bits in a string must be chosen *a priori* based on the required precision of the solution. As the precision increases, so does the length of the string, which will increase the complexity of the problem presented to the GA (Deb, 2002). In addition, certain strings, such as 0111 and 1000, require the alteration of many bits to mutate to a nearby solution, which is highly unlikely. Thus, the GA is more likely to be trapped in a local optimum rather than converge to the global optimum (Deb, 2002). On the other hand, for some strings the alteration of only one bit can cause a significant change to the decision variable value, for example from 0000 to 1000. This can also overshadow the ability of GAs converging to global optima.

In order to address the concerns about the binary coding scheme, other coding schemes, such as real numbers and integers, are also used. Strings coded in real numbers allow GAs to operate on decision variables having continuous values directly, which may improve the performance of GAs by exploiting the graduality of the objective functions (Herrera et al., 1998). However, different crossover and mutation operators are required for real-coded GAs (Herrera et al., 1998). An integer coding scheme can solve the redundancy problem of the binary coding scheme, which suits problems with a discrete search space, such

as WDS optimization problems. In addition, an integer string allocates only one bit to each decision variable. Therefore, crossover cannot occur within an integer decision variable, which may break up good solutions that have been identified, as it does to a binary-coded decision variable (Gibbs, 2008). However, due to the less disruptive nature of inter-coded strings, a higher mutation probability may be required in order to explore the search space more effectively (Gibbs, 2008).

Apart from the real-coded strings, binary- and integer-coded strings themselves are rather meaningless outside the genetic operators. They need to be decoded in order to link the locations of the solutions they represent in the search space to the real world problem to which the GA is presented. Therefore, string decoding generally refers to the process of translating genetically represented strings back to their real world values on which the objective function evaluation is based. Both real number and integer coding schemes are used in the Water System Multiobjective Genetic Algorithm (WSMGA) developed for this research.

3.1.2 Population initialization

In a GA, a group of solutions called a population is optimized simultaneously in each generation. The parent populations before the first generation are normally generated randomly at the population initialization step. In this step, a uniform random number generator can be used to generate random numbers within the range of 0 and 1. By transferring this randomly generated number to the range of the decision variables (binary, real number or integer), the value of a decision variable is generated. The initial population is generated by repeating this process for each decision variable of a string and for each string in the population.

3.1.3 Objective function evaluation

The formulation of objective functions in GAs is problem dependent. For example, if the problem is to minimize the cost of a pipe network, the objective function involves calculating the total cost of the pipe network by adding up the cost of each pipe. In a GA, the objective function always needs to be either maximized or minimized to suit the application mechanisms of the algorithm. Quite often, simulation models are required in the objective function evaluation process to assist the estimation of constraint violation and objective function values of each trial solution. For the case of WDS optimization, a hydraulic simulation model, which can mathematically imitate the behavior of a WDS, is required. In this research, a commonly used hydraulic simulation model called EPANET2 (Rossman, 2000) is used. In addition, in traditional GAs constraints are handled by using a penalty coefficient, which penalizes the solutions that violate constraints by increasing the objective function values for a minimization problem or decreasing the objective function values for a maximization problem (Goldberg, 1989). Thus, a constrained problem is transferred into an unconstrained problem.

3.1.4 Selection

The first genetic operator in a GA is the selection operator. The objective of selection is to increase the number of good solutions in the next generation. There are many selection methods, and all of them rely on the principle of “survival of the fittest”. Among these methods, tournament selection has been proven to have good growth and convergence properties (Deb, 2002) and is therefore used in the WSMGA. Before tournament selection, two copies of each string will be placed in the mating pool, from which the candidates for the tournaments are selected randomly. In each tournament selection, the string with better objective function value is selected, and the selection for each pair of strings is considered in turn. Therefore, after the selection process, the fittest string from the population has two copies in the

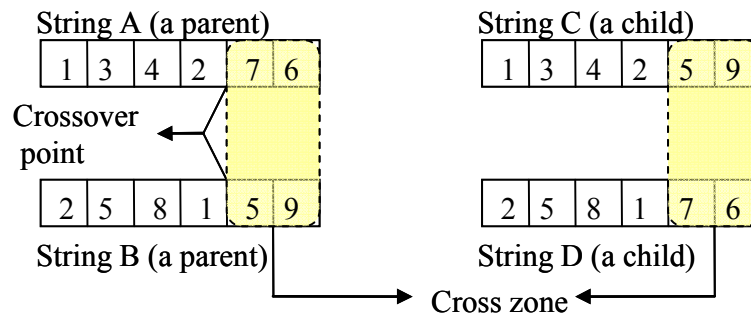


Figure 3.2 One-point crossover applied to two integer strings

mating pool, while the string with the worst fitness is eliminated, and the population size is kept the same.

3.1.5 Crossover (mating)

The second genetic operator in a GA is the crossover operator (mating), which is the process for producing offspring strings from parent strings. Crossover combines solutions that have been identified previously for having desired characteristics and attempts to produce new solutions that will retain the desired characteristics from both parents.

When applying the crossover operator, the population is divided into groups of two strings, and each pair of strings is considered in turn. The most common crossover operator is a simple crossover, where parts of the two parent strings are interchanged at one or multiple crossover points, either selected randomly or specified by the user (e.g. uniform crossover). The simple crossover operators were originally designed for binary-coded strings; however, they can be applied to integer-coded strings with no modifications. A simple one-point crossover operator for integer strings, which is used in the WSMGA, is illustrated in Figure 3.2. The crossover operator is applied to two six-bit parent strings A and B. The bits after a crossover point on strings A

and B are interchanged, thus two child strings C and D are generated. For real-coded string, different crossover operators, such as simulated binary crossover (Deb, 2002), are required.

The probability of crossover is chosen by the user by specifying a crossover probability parameter p_c , which often ranges from 0.5 to 1. After the crossovers have been performed, $(100 \times p_c)\%$ pairs of strings in the parent generation are replaced by their child strings and the population is updated.

3.1.6 Mutation

The third genetic operator in a GA is the mutation operator, the role of which is to introduce diversity to the search process to prevent premature convergence of GAs to local optima. For any GA, mutation can be applied simply by changing the value of the bit to which mutation is applied. There are two common mutation operators: bitwise mutation and adjacency mutation. Bitwise mutation can be used to restore lost good solutions and improve exploration of the search space (Herrera et al., 1998). Adjacency mutation can be used to finely tune solutions that have been identified (Gibbs, 2008).

Bitwise mutation and adjacency mutation for integer strings, which are both coded in the WSMGA, are illustrated in Figure 3.3. When bitwise mutation is applied to a bit (a decision variable in an integer solution string), an option for the decision variable represented by the bit is selected randomly. For the example in Figure 3.3, bitwise mutation is performed on the third bit of string A and number 8 is randomly selected between zero and the number of options for the decision variable. Thus, string C is generated. When adjacency mutation occurs, the value of a bit is only able to mutate to the two adjacent values of its current value, often with equal probability. For example, if the value of a bit is 7, when adjacency mutation occurs, the value of the bit has 50% probability to mutate into 6 and 50% probability to mutate into 8. As the second example in Figure 3.3 shows, when adjacency mutation happens to

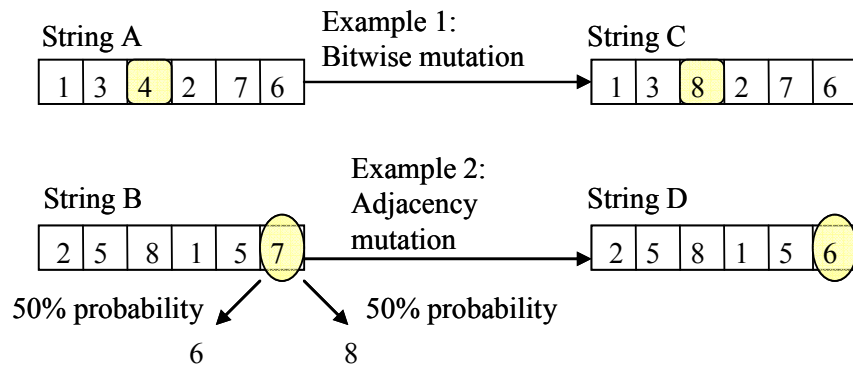


Figure 3.3 Bitwise mutation and adjacency mutation for integer strings

the last bit of string B, the value of that bit is mutated to 6, and thus string D is generated.

Similarly to the crossover operator, the probability of mutation is also selected by the user by specifying a mutation probability parameter p_m . After the mutation process, $(100 \times p_m)\%$ bits in the total $n \times m$ (where, n is the number of decision variables and m is the population size) number of bits are mutated.

3.1.7 Stopping criteria

In a GA, stopping criteria are required to stop the optimization process. The most common stopping criterion is the number of generations that need to be evaluated. Other stopping criteria include the variance of objective function values within a generation being less than a specified value and the execution time.

3.2 Multiobjective genetic algorithms

3.2.1 Moving from single-objective to multiobjective genetic algorithms

In traditional optimization problems, there is only one fitness/objective function to be evaluated in the optimization process. Optimization algorithms will either maximize or minimize the objective function value. A single-objective GA can be used to solve these problems. However, most optimization problems in the real world have multiple objectives that need to be satisfied. Therefore, a number of methods, such as the Weighted Sum Method, ϵ -Constraint Method, Weighted Metric Method, Benson's Method, Value Function Method, Goal Programming Methods and Interactive Methods have been developed to assist single-objective GAs in solving multiobjective problems (Deb, 2002). All of these methods, however, deal with multiobjective optimization problems by using a single-objective approach, in which the multiple objectives are converted into one objective in some way. As a result, they have a number of significant drawbacks: 1) they are not able to search the true objective space and therefore, lose the tradeoff information among the objectives (Singh et al., 2003); 2) they are only able to find one optimal solution in each simulation run; 3) not all of these methods guarantee finding all optimal solution sets of non-convex optimization problems; and 4) most of these methods require explicit knowledge of the optimization problem (Deb, 2002). Therefore, a real multiobjective GA is required in order to solve real world optimization problems with multiple objectives, such as WDS optimization problems.

3.2.2 Development of multiobjective genetic algorithms

The first real multiobjective GA – Vector Evaluated Genetic Algorithm (VEGA) – was proposed by Schaffer (1985). VEGA is a simple extension of a single-objective GA for multiobjective optimization problems. In VEGA, an

objective vector is used in place of the objective function used in a single-objective GA. Each element of the vector represents an objective function. The GA population is divided into equally sized subpopulations according to the number of objectives. For each subpopulation, only one element of the objective vector is evaluated. VEGA is implemented using a non-Pareto approach (Savic, 2002) in which each subpopulation is evaluated against one objective only. Thus, the solutions with one optimal objective are likely to be preferred (Deb, 2002).

A few years after the development of VEGA, Hajela and Lin (1992) introduced a Weight-based Genetic Algorithm (WBGA). The WBGA is similar to the Weighted Sum Method in that the sum of the weighted objective function values is used to evaluate potential solutions. However, instead of using one weight vector as in the Weighted Sum Method, each individual in a generation is assigned a different weight vector. Thus, multiple optimal solutions can be found in a single simulation run. However, the WBGA has difficulties in dealing with mixed types of objective functions (both minimization and maximization) and finding non-convex Pareto-optimal solutions (Deb, 2002).

In the same year that WBGA was introduced, Fonseca and Fleming (1993) proposed a multiobjective GA called the Multi-objective Genetic Algorithm (MOGA). In Fonseca and Fleming's MOGA, the concept of non-domination was first introduced (Deb, 2002). In addition, the concept of niching (Oei et al., 1991) was used to maintain the diversity of non-dominated solutions. However, as solutions in the same non-dominated front (except for the first front) are assigned the same rank, an unwanted bias may be introduced towards some solutions (Deb, 2002). Niching also introduces an extra sharing parameter, which needs to be defined *a priori* (Deb, 2002).

In 1994, Srivinas and Deb (1994) introduced the Non-dominated Sorting Genetic Algorithm (NSGA), in which the non-domination concept was implemented directly. However, the non-dominated sorting algorithm used in the NSGA has a computational complexity of $O(MN^3)$, where M is the

number of objective functions and N is the population size (Deb et al., 2002). This raises an efficiency problem, especially when a large population is used. A sharing function method (Goldberg and Richardson, 1987) was used in the NSGA to maintain the diversity of non-dominated solutions. Therefore, NSGA also requires a sharing parameter, as is the case for Fonseca and Fleming's MOGA. It has also been found that NSGA is sensitive to the value of the sharing parameter (Srinivas and Deb, 1994).

There are a number of concerns with most multiobjective GAs developed by the early 1990s. The first concern is the high computational complexity [$O(MN^3)$] of the non-dominated sorting methods used in these multiobjective GAs, which exponentially increases computational time for large population sizes. The second concern is the lack of elitism. Elitism guarantees that a good solution found early on in the population will never be lost. Consequently, elitism makes sure the fitness of the population does not deteriorate, and it can also improve convergence and significantly speed up GAs (Deb et al., 2002). The third concern is that the need of a sharing parameter increases the number of parameters in a traditional multiobjective GA.

In order to overcome the disadvantages of previous multiobjective GAs, a fast and elitist non-dominated sorting genetic algorithm – NSGA-II – was developed by Deb et al. (2000). The details of NSGA-II are presented below.

3.2.3 NSGA-II

In addition to the conventional steps of genetic algorithms, such as selection, crossover and mutation, NSGA-II has four special features, which address the concerns over traditional multiobjective GAs.

First of all, a special book-keeping strategy is used in the non-dominated sorting process of NSGA-II. Instead of repeatedly ranking the dominated solutions in the population for each rank, every solution in the population is checked with a partially filled dominating population until the partially

dominating population grows to include all non-dominated solutions. In this approach, the maximum computation required for the non-dominated sorting of the entire population is of $O(MN^2)$ instead of $O(MN^3)$, which reduces computational complexity significantly. Secondly, instead of ranking the parent population only, as in traditional multiobjective GAs, a global population, which combines both the parent and child populations, is ranked in NSGA-II. This global population guarantees that good solutions in the parent population will not be lost due to crossover or mutation, thus elitism is introduced into the algorithm. Thirdly, a crowding distance comparison is used to compare solutions within the same rank to maintain the diversity of non-dominated solutions; hence, a sharing parameter is not required.

Furthermore, the traditional constraint handling method used by most GAs is not very effective and requires specification of the value of an additional parameter (Vairavamoorthy and Ali, 2000). An efficient constraint handling method (Deb, 2000) based on tournament selection and referred to as constrained tournament selection (Deb, 2002) is used in NSGA-II. In this tournament selection, the feasibility and constraint violation of each solution are first checked against all constraints. A solution x is said to dominate a solution y , if any of the following is true (Deb, 2000):

1. Solution x is feasible and solution y is infeasible;
2. Solutions x and y are both feasible, but solution x has a smaller fitness function value (minimizing fitness function value is assumed);
3. Solutions x and y are both infeasible, but solution x has a smaller constraint violation.

In this way, a penalty coefficient is not required and feasible solutions always have priority over infeasible solutions.

3.3 WSMGA

For the purpose of this research, a multiobjective GA called the Water System Multiobjective Genetic Algorithm (WSMGA) has been developed based on NSGA-II. The special book-keeping strategy based non-dominated sorting, the global population-based elitism preservation algorithm, the crowding distance-based diversity maintenance strategy and the constrained tournament selection used in NSGA-II are all adopted in WSMGA. In order to cater for discrete decision variables generally encountered in WDS optimization problems, the traditional binary coding scheme used in NSGA-II has been replaced by an integer coding scheme in WSMGA, while the option of using real number inputs in NSGA-II has been preserved. As a result, the crossover and mutation operators for the binary coding scheme used in NSGA-II are also revised to accommodate the integer coding scheme in WSMGA, as discussed previously. In order to avoid the loss of optimal solutions due to crossover and mutation, an archive strategy used in SPEA2 (Zitzler et al., 2002) is also incorporated into the development of WSMGA to keep a record of all optimal solutions generated in the optimization process. In addition, the output function in WSMGA is specifically developed to record WDS network. The WSMGA source code and example input files and UNIX scripts used in this research are attached in Appendix A.

To validate its performance, WSMGA has been tested by benchmarking it against NSGA-II using a number of test functions used in Deb et al. (2002). In order to ensure a fair comparison, real number inputs were used for both algorithms. The test functions used and comparison results are summarized in Appendix B.

Chapter 4

Synopsis of Publications

This chapter discusses the contributions of the six journal publications presented in subsequent chapters of this thesis. The overall aim of this study is to incorporate the minimization of the leading environmental concern – greenhouse gas (GHG) emissions - as one objective into the optimal design of WDSs via a multiobjective approach, together with the traditional economic objective of minimizing life cycle cost and the reliability objective of maximizing the hydraulic reliability of WDSs. In order to do so, ten research aims, listed in Section 1.2, have been identified. Figure 4.1 illustrates the relevance of the six journal publications and their contents to the ten research aims of this research.

The development of a framework to incorporate the life cycle GHG emissions into WDS optimization via a multiobjective approach (Aim 1) is included in Publication 1. Publication 1 also investigates the tradeoffs between the economic objective of minimizing the life cycle cost and the environmental objective of minimizing life cycle GHG emissions (Aim 2) and the sensitivity of these tradeoffs to the discount rate used in the objective function evaluation process (Aim 3). Publication 2 addresses the issue related to the introduction of an emissions trading scheme, which may undermine the incentive of using a multiobjective approach to account for GHG emissions of WDSs by providing an alternative single-objective approach (Aim 4). Publication 3 first solves a technical issue of incorporating both fixed speed pumps (FSPs) and variable speed pumps (VSPs) into the design optimization of WDSs by

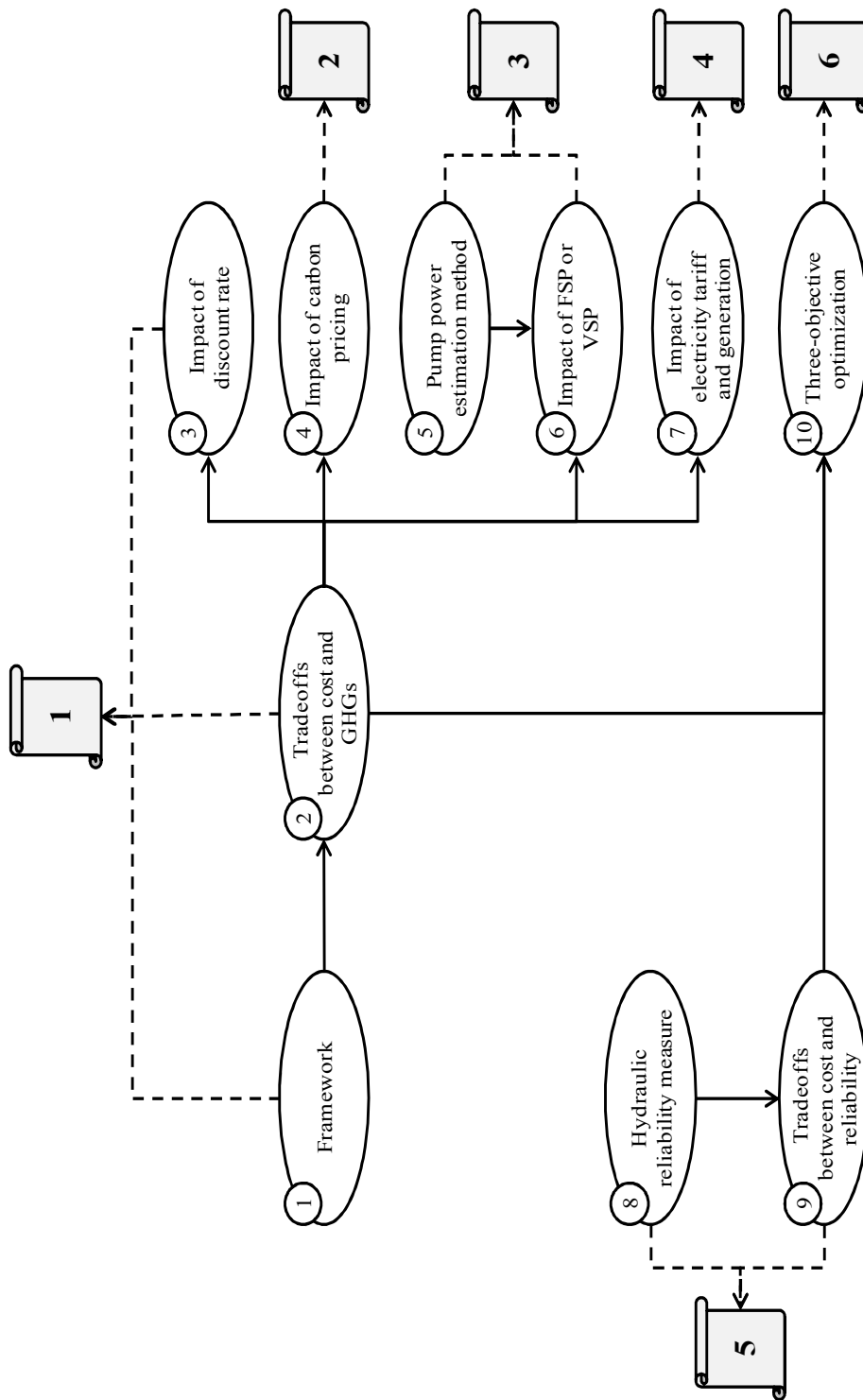


Figure 4.1 Contribution of the six journal publications presented in this thesis in relation to the ten research aims

presenting the development of a generic pump power estimation method (Aim 5). It then explores the impact of the use of VSPs instead of FSPs on WDS optimization accounting for GHG emissions (Aim 6). The seventh research aim of exploring the impact of electricity tariffs and generation on WDS optimization accounting for GHG emissions is included in Publication 4. In publication 5, the suitability of a hydraulic reliability measure called surplus power factor (Vaabel et al., 2006) for WDSs involving pumping water into storage facilities is validated (Aim 8). Thereafter, the tradeoffs between the economic objective of minimizing life cycle cost and the objective of maximizing hydraulic reliability represented using the surplus power factor for WDS optimization are explored (Aim 9). The last publication (Publication 6) investigates the impact of the inclusion of the hydraulic reliability objective on multiobjective WDS optimization accounting for the economic objective of minimizing life cycle cost and the environmental objective of minimizing GHG emissions and explores the interaction of the three objectives in a three dimensional space (Aim 10). The details of these six journal publications are presented in this chapter.

Publication 1 describes the formulation of the multiobjective problem of WDS optimization accounting for the minimization of life cycle economic cost and the minimization of life cycle GHG emissions and explores the tradeoffs between the economic and environmental objectives (Aims 1 and 2). As WDSs are social infrastructure with a long life span (e.g. 100 years or longer), the costs (e.g. operating costs and emissions) of WDSs will occur over a long period of time. Present value analysis (PVA) is required in order to take into account the time preference of these costs, thereby enabling costs occurring at different times to be compared. A number of important issues involved in the selection of the discount rate for the economic and environmental objective evaluation are also included in Publication 1 (Aim 3). The first issue is the selection of the discount rate for evaluating the economic and environmental objectives. The selection of the value of the discount rate has a significant impact on the outcomes of PVA and thus the value of the objective functions. For example, a high positive discount rate (e.g. 8% or above) results in ongoing costs to diminish from around 50 years onwards; a

low positive discount rate close to zero (e.g. 1.4%) will only halve the impact of the costs occurring at the 50th year; and a zero discount rate suggests that the costs occurring at any time into the future are as important as the costs occurring at present. The impact of the discount rate used in PVA for objective function evaluation is investigated in the paper by using a range of discount rates used for social projects selected from literature.

The second issue is whether or not ongoing environmental costs (e.g. GHG emissions due to energy consumption for system operation) should be discounted the same as ongoing economic costs. This is a controversial issue and there is no universally accepted resolution. In Publication 1, this issue is addressed by using two discount scenarios. In discount scenario 1, economic costs are discounted at various discount rates, while a zero discount rate is always used for the calculation of life cycle GHG emissions. In discount scenario 2, both economic cost and GHG emissions are discounted at the same rate. In addition, details of the Water System Multiobjective Genetic Algorithm (WSMGA), which is the multiobjective optimization program developed for this research, are included in Publication 1.

The major contribution of Publication 1 is that the minimization of GHG emissions is incorporated into the optimization of WDSs via a multiobjective approach for the first time. The optimization results presented in the paper demonstrate that a reasonable and acceptable increase in the economic cost can often result in a substantial reduction in GHG emissions, which provides an avenue for reducing the carbon footprint of the water industry. The optimization results also show that a lower discount rate for evaluating the life cycle economic cost, such as the 1.4% recommended by Sir Nicolas Stern (2006), can remove some solutions with high GHG emissions (and low cost) from the Pareto-optimal front generated for discount scenario 1, which can potentially result in low emission WDS designs. Another contribution of Publication 1 is the development of the concept of carbon cost slope (see Figure 5.5), which is expressed as the increase in economic cost in terms of every unit reduction in GHG emissions, is also developed. This carbon slope

concept can be used to compare the effectiveness of reducing GHG emissions from selecting different Pareto-optimal solutions.

Publication 2 addresses the major issue of using a multiobjective approach for WDS optimization accounting for GHG emissions under an emissions trading scheme, where carbon emissions are priced (Aim 4). When a monetary value (or carbon price) is assigned to GHG emissions upon the introduction of an emissions trading scheme with a cap and trade approach, the GHG emissions in tonnes can be converted into monetary terms, which enables a single-objective approach to be used. This raises the question of whether the introduction of carbon pricing under an emissions trading scheme will make use of a multiobjective optimization approach obsolete or whether such an approach can provide additional insights that are useful in a decision-making context. In the paper, this question is answered by comparing single- and multiobjective approaches for WDS optimization under a range of different carbon prices.

With the aid of two case studies, Publication 2 demonstrates that a single-objective optimization approach is easier to implement, requires less computational effort and results in a simpler decision-making process. However, a single-objective approach also leads to a loss of tradeoff information between the two competing objectives, the introduction of uncertainties involved in carbon pricing and a controversial, unpopular assumption - perfect substitutability, in which one dollar's worth of damage caused by GHG emissions can be compensated for by a dollar's worth of economic growth (Stern and Persson, 2007). In contrast, the multiobjective approach provides decision makers with more detailed information by explicitly showing the tradeoffs between the two objectives. As the carbon price has no impact on the tradeoffs between the two objectives, the carbon pricing process can be removed from the objective function evaluation process and result in multiobjective solutions that express the tradeoffs between economic cost in dollars and GHG emission in tonnes. Based on these tradeoffs, a carbon cost mapping expressed in terms of the dollar cost of reducing one tonne of GHG emissions can be obtained. This carbon cost

mapping can then be used to determine the single-objective optimal solution for a given market carbon price within the set of Pareto-optimal solutions obtained using the multiobjective approach without any additional optimization runs. Thus, apart from the tradeoff information, the optimization results obtained using the multiobjective approach provide decision makers with a clear indication of the relative effectiveness of the selected carbon price in reducing GHG emissions relative to other carbon prices. Publication 2 concludes that a multiobjective approach considering the economic cost in dollars and GHG emissions in tonnes should be used for optimizing WDSs accounting for GHG emissions, even under an emissions trading scheme where GHG emissions can be traded based on a carbon price.

As mentioned previously, GHG emissions are mainly generated from system operation related to pumping when electricity is sourced from fossil fuels within the water industry (Kelly, 2007). In traditional WDSs involving pumping, FSPs are commonly used due to their lower capital costs compared with those of VSPs. However, VSPs provide easier control over the system, which enables a better response to abnormal situations, such as fire and breakage. More importantly, pressure or flowrates can be maintained very close to minimum allowable levels by using VSPs. Thus, there is great potential for saving energy and hence for reducing GHG emissions from WDSs by switching from FSPs to VSPs (Aim 6). This potential is explored in **Publication 3** in conjunction with multiobjective optimization.

In previous research on WDS design optimization, only FSPs were used. This is not only because FSPs are commonly used in existing WDSs, but also because FSPs can be easily simulated in an optimization process by using a fixed pumping head or a pump curve (Duan et al., 1990; Fillion, 2009; Wu et al., 2010b), whereas the dynamic features of VSPs make their simulation within optimization iterations a more difficult task. A major technical contribution of **Publication 3** is the development of a pump power estimation method, which makes possible the incorporation of VSPs in an iterated optimization process (Aim 5). This method makes use of a flow control valve and can be implemented using a hydraulic solver, such as EPANET

(Rossman, 2000), through a false position based optimization approach. It is suited to fast and repeated estimation of operating energy consumption of a large number of network configurations, and the generic nature of this method ensures that different network configurations generated during the optimization process are compared fairly.

Publication 3 demonstrates the application of the pump power estimation method with one case study. The optimization results of the case study show that the use of VSPs instead of FSPs in multiobjective WDS optimization accounting for both economic cost and GHG emission minimization can reduce both the economic cost and GHG emissions of optimal solutions. The effectiveness of replacing FSPs with VSPs in reducing operating costs and emissions is more significant for systems with smaller-diameter pipes due to their higher dynamic heads (friction losses) relative to static heads. As a result, the use of VSPs in multiobjective WDS optimization leads to optimal solutions that are both cheaper in terms of economic cost and GHG emissions. Based on the results presented in Publication 3, it can be concluded that switching from fixed-speed pumping to variable-speed pumping can be an effective method for reducing both cost and GHG emissions of WDSs when used in conjunction with multiobjective optimization.

Currently, most water utilities and energy producers operate independently and water utilities have little control over electricity tariffs and generation. However, the water and energy industries are closely related: a large amount of water is needed for energy production and a large amount of energy is needed for treatment, transmission and distribution of water. In addition, electricity tariffs have a significant impact on the operating cost of WDSs. Emission factors, which depend on the mix of the sources of electricity in a region, such as combustion of fossil fuel or nuclear, solar and hydroelectric energy, directly dictate the ongoing operating emissions from WDSs in that region. Therefore, both electricity tariffs and emission factors have a significant impact on the results of multiobjective WDS optimization accounting for economic cost and GHG emissions. **Publication 4** explores the water-energy nexus and its impact on the tradeoffs between the economic cost

and GHG emissions from WDSs by investigating the sensitivity of the tradeoffs to the above two key factors – the electricity tariffs and emission factors, in the objective function evaluation process (Aim 7).

As part of the sensitivity analysis in Publication 4, realistic ranges and changing trends of electricity tariffs and emission factors are estimated based on data from Australia. Two different scenarios and five combinations of the two factors are considered in the sensitivity analysis. The results from the sensitivity analysis show that the electricity tariffs into the future have no impact on the total GHG emissions of a particular WDS; however, a higher electricity tariff into the future can remove some network solutions with high GHG emissions from the Pareto-optimal front. In contrast, the emission factor appears to have little impact on the network configurations of the Pareto-optimal solutions; as expected, however, it has a significant impact on the total GHG emissions from WDSs.

Publication 4 also demonstrates that selection of the design horizon has an impact on the results of multiobjective optimization of WDSs accounting for economic cost and GHG emission minimization. A shorter design horizon, such as 50 years or less, will reduce the future impact of WDSs, which will in turn favor networks with smaller capital costs but higher GHG emissions, when a low discount rate such as 1.4% is used. On the other hand, a longer design horizon (e.g. 100 years) makes accurate projection of electricity tariffs and emission factors into future difficult, and can introduce higher levels of uncertainties into the optimization process.

Publication 5 first introduces the concept of the surplus power factor developed by Vaabel et al (2006) into multiobjective optimization of WDSs accounting for economic cost and reliability as a network reliability measure. The surplus power factor is a useful reliability measure, particularly for WDSs involving pumping water into reservoirs or tanks, which are often the primary cause of GHG emissions. For these WDSs traditional reliability measures often cannot be used, as the calculation of the traditional measures rely on the difference between the required and minimum allowed pressure heads at the

outlets of the systems. The suitability of the surplus power factor as a hydraulic reliability measure for WDSs is assessed by comparing it with a number of existing WDS hydraulic reliability measures (Aim 8), such as the minimum surplus head (Gessler and Walski, 1985), the resilience index (Todini, 2000) and the modified resilience index (Jayaram and Srinivasan, 2008) for a number of benchmark case studies, including the two loop network studied by Abebe and Solomatine (1998), Todini (2000) and Prasad and Park (2004), the New York tunnel problem (Schaake and Lai, 1969) and the Hanoi problem (Zecchin et al., 2006). Thereafter, the applicability of the surplus power factor as a reliability measure for WDSs involving pumping is demonstrated using the three-tank water transmission system (WTS) case study investigated in Publication 2. Finally, Publication 5 explores the tradeoffs between the economic objective of minimizing the cost and the hydraulic reliability objective of maximizing the surplus power factor of WDSs via multiobjective optimization (Aim 9).

The introduction of the surplus power factor developed by Vaabel et al (2006) as a hydraulic reliability measure for WDSs in Publication 5 makes the optimization of hydraulic reliability possible for WTSs, or WDSs including pumping water into storage facilities. The optimization results presented in Publication 5 also demonstrate that there are significant tradeoffs between the minimization of economic cost and the maximization of network hydraulic reliability represented by the surplus power factor of WDSs. Often, with a small increase in the total economic cost, the reliability level of the final selected network can be increased significantly.

Publication 6 is the final publication in this thesis. It investigates the impact of the inclusion of the hydraulic reliability objective of maximizing surplus power factor on WDS optimization accounting for the economic objective of minimizing life cycle cost and the environmental objective of minimizing GHG emissions and explores the interaction of the three objectives in a three dimensional space (Aim 10). The optimization results presented in Publication 6 show that the Pareto-optimal front resulting from optimizing the three objectives is largely dominated by the tradeoffs between the economic

objective and the hydraulic reliability objective. Consequently, the inclusion of the third hydraulic reliability objective introduces a large number of solutions into the Pareto-optimal front in addition to the optimal solutions expressing the tradeoffs between the economic objective of minimizing life cycle cost and the environmental objective of minimizing life cycle GHG emissions. These solutions are generally more expensive, but have significantly improved hydraulic reliability levels. More importantly, it has been found that by including the hydraulic reliability, the optimization can lead to network solutions that are more practically feasible to implement and with reasonable cost and reduced GHG emissions.

The optimal design of WDSs has always been a multiobjective problem. However, the economic objective has often outweighed the other objectives in the field of WDS optimization research. Reliability considerations are more often than not incorporated into the optimization of WDSs as constraints, rather than design objectives. The leading environmental concern of GHG emissions was not considered at all until the realization of the urgency of reducing carbon footprints from every aspect of society, including the water industry. In addition, recent technological advances have made multiobjective optimization techniques, such as multiobjective genetic algorithms, available for WDS optimization. Now is the perfect time to make the optimal design of WDSs considering not only the traditional economic objective, but also the environmental objective of minimizing GHG emissions and the reliability objective of maximizing hydraulic reliability simultaneously, a reality. The following six chapters present the six journal publications included in this research.

Chapter 5

Accounting for Greenhouse Gas Emissions in Multiobjective Genetic Algorithm Optimization of Water Distribution Systems

Publication 1

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Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.

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Abstract

Considerable research has been carried out on the optimization of water distribution systems (WDSs) over the last three decades. In previous research, attention has mainly focused on the minimization of cost, due to the high expenditure associated with the construction and maintenance of such systems. However, the impacts of WDSs on the environment usually have not been considered adequately. The recent increasing awareness of sustainability and climate change, especially global warming, has led to research where greenhouse gas (GHG) emissions are considered. In the study described in this paper a multiobjective genetic algorithm for WDS optimization has been used as an explorative tool to investigate the tradeoffs between the traditional economic objective of minimizing costs and an additional environmental objective of minimizing GHG emissions. The impacts of minimizing GHG emissions on the results of WDS optimization have been explored for a case study in this paper. The results indicate that the inclusion of GHG emission minimization as one of the objectives results in significant tradeoffs between the economic and environmental objectives. Furthermore, a sensitivity analysis has been conducted by using different discount rates in a present value analysis for computing both ongoing costs and GHG emissions. The results obtained show that the Pareto-optimal front is very sensitive to the discount rates used. As a result, the selection of discount rates has a significant impact on final decision making.

5.1 Introduction

Water distribution systems (WDSs) are essential parts of urban infrastructure systems, as they deliver water from water sources to domestic, commercial, and industrial water users to maintain their daily activities. Due to the large scale and complexity of WDSs, optimization techniques are often used in the planning and design of such systems. Traditionally, the optimization of WDSs has focused on minimizing the cost of the system (Simpson et al., 1994). However, an increasing awareness of sustainability has led to consideration of other objectives.

The concept of sustainable development was first brought to the attention of the international community through the Brundtland report *Our Common Future* in 1987. Since then, the concept of sustainability has been widely accepted. However, the main difficulty lies in transforming the principles of sustainability into operational models, for example, incorporating sustainability into the design and construction of urban infrastructure systems (Sahely et al., 2005). To tackle this challenge, a number of studies have developed methods of evaluating sustainability of urban infrastructure systems (Hiesl et al., 2001; Sahely et al., 2005; Sahely and Kennedy, 2007; Filion, 2008). In these studies, a number of environmental criteria, such as the minimization of energy usage, minimization of chemical usage, minimization of greenhouse gas (GHG) emissions and minimization of sludge disposal have been identified as key elements in improving the sustainability of urban infrastructure systems and urban water systems.

While reference to multiobjective optimization has appeared in the literature since the late 1960s (Schaake and Lai, 1969), in engineering applications, sustainability related issues such as pumping energy cost (Ilich and Simonovic, 1998), social cost (Dandy and Hewitson, 2000), water quality (Dandy and Hewitson, 2000), and material usage (Dandy et al., 2006) have only been introduced into the optimization of WDSs over the past 10 years or so. In the study carried out by Dandy et al.(2006), the GHG emissions

resulting from pipe manufacturing were evaluated for two different designs of a WDS. To the writers' knowledge, the Dandy et al. (2006) study was the first time that GHG emissions have been evaluated for a WDS design problem in a published paper.

The study described in this paper incorporates the environmental criterion of minimizing total GHG emissions into the optimization of WDSs as an objective, along with the conventional economic objective of minimizing the cost of the system. A multiobjective genetic algorithm has been used in this paper as an explorative tool to investigate the tradeoffs between the economic and environmental objectives. In the evaluation of the objective functions, both the capital costs and GHG emissions that occur due to initial manufacture and construction of the system and the operational costs and emissions during the design life of the system are taken into account. To properly assess the sustainability of a WDS, a comprehensive analysis of multiple environmental discharges (for example GHG emissions, air pollution and solid waste production, etc.) would need to be carried out. Care needs to be taken when reducing the number of environmental streams to be considered in the analysis (as is presented in this paper to demonstrate the multiobjective optimization methodology) that environmental problem shifting does not occur.

To account for the time preference involved in objective function evaluation, an appropriate means of accounting for future costs and emissions has to be used. In economics, this is generally achieved by using present value analysis (PVA) or discounting (Tietenberg, 1997). For private projects, discount rates are often calculated based on market interest rates. As a result, a relatively highly decreased value is placed on the costs and benefits to future generations (Rambaud and Torrecillas, 2005). However, when dealing with social projects, such as WDSs, which have a long design life, or whose environmental effects due to GHG production, for example, will potentially be spread out over hundreds of years, careful consideration needs to be given to selecting an appropriate discount rate. As the selection of appropriate discount rates for social projects remains a controversial issue, a set of

different discount rates selected from literature has been employed in this paper for evaluation of the objective functions. Optimization results obtained using different discount rates are compared to explore the sensitivity of WDS optimization outcomes to different discount rates.

The remainder of the paper is organized as follows. In the next section, the methods used in this study, including multiobjective optimization, PVA, and social discounting are introduced. Thereafter, the formulation of the problem is presented. The tradeoffs between the economic and environmental objectives are then explored for a case study. The impact that different discount rates have on WDS optimization results is also investigated. Finally, the conclusions are presented.

5.2 Methods

5.2.1 Multiobjective optimization

To optimize WDSs accounting for both the economic and environmental objectives, a multiobjective approach is required. A multiobjective approach can be implemented by using a number of different algorithms. Among these algorithms, genetic algorithms have been shown to be effective in solving WDS optimization problems in a study conducted by Simpson et al. (1994)(1994). Since then, genetic algorithms and later multiobjective genetic algorithms have been used successfully in solving WDS optimization problems (Savic, 2002; Farmani et al., 2005; Keedwell and Khu, 2006; Jayaram and Srinivasan, 2008).

In this study, a multiobjective genetic algorithm called water system multiobjective genetic algorithm (WSMGA) was developed based on one of the “state-of-the-art” multiobjective genetic algorithms, NSGA-II (Deb et al., 2002). The optimization procedure using NSGA-II is summarized in Figure

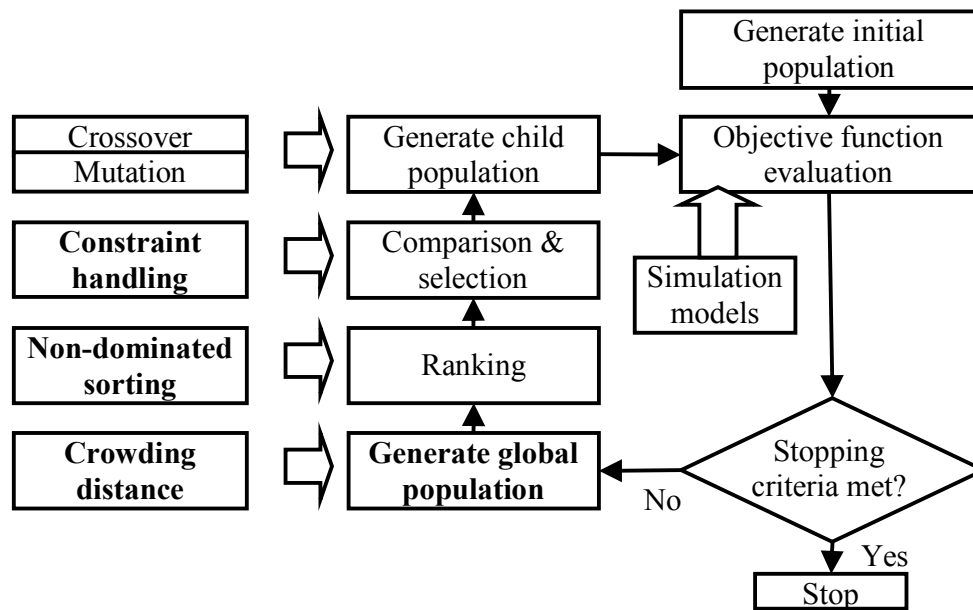


Figure 5.1 Optimization process using multiobjective genetic algorithm NSGA-II

5.1. In addition to the conventional steps of genetic algorithms, such as selection, crossover, and mutation, NSGA-II has four special features (shown in bold in Figure 5.1), which distinguish it from traditional multiobjective genetic algorithms. First of all, before applying the ranking operation, a global population is generated by combining both the parent and child generations, thus elitism is ensured. Second, a special book-keeping strategy is used in the non-dominated sorting process, which reduces computational complexity. In addition, a crowding distance comparison is used for solutions with the same rank; hence a sharing parameter is not required. Furthermore, an efficient constraint handling method referred to as constrained tournament method (Deb, 2002) is used. In this type of tournament selection, the need for a penalty coefficient is removed and feasible solutions are always given priority over infeasible solutions. WSMGA has adopted these four features. In addition, in WSMGA the traditional binary coding scheme in NSGA-II has been modified to handle integer values, which caters for discrete decision

variables generally encountered in WDS optimization problems; while the option of using real number inputs in NSGA-II has been preserved. To validate its performance, WSMGA was tested by benchmarking it against NSGA-II using a number of the test functions in Deb et al. (Deb, 2002), for which real number inputs were used.

In the multiobjective optimization analysis formulation proposed in this paper a number of assumptions are made and parameter values are assumed. Consequently, in real design situations, the sensitivity of the optimal solutions to these parameters should be tested by varying the uncertain parameters and carrying out further optimization runs. The designer must then make a judgment from a range of results as to which design is most appropriate.

5.2.2 Present value analysis

PVA is essential in any economic or financial analysis. With an appropriate discount rate, PVA translates values from the future to the present, enabling effects occurring at different times to be compared (Kaen, 1995). The present value (PV) of a future payment can be calculated using the following equation:

$$PV_t = \frac{C}{(1+i)^t} \quad (5.1)$$

where C is the payment at a given future time; t is the number of time periods; and i is the discount rate. Therefore, PV_t is the PV of a future payment at the end of the t th time period. In this equation, $1/(1+i)^t$ is the discount factor that represents the extent of the reduction that occurs when a future payment to be received at time t is translated into its PV. The selection of the value of discount rate i is important, as it has significant impact on the results of PVA. When dealing with private projects, the discount rate is usually based on the marginal productivity of capital (Dasgupta et al., 1999). However, in the case of dealing with social/public projects, discount rates

based on social cost-benefit analysis/social discounting are recommended (Rambaud and Torrecillas, 2005).

5.2.3 Social discounting

Selection of discount rates, especially for social projects, is a very complex issue. Rambaud and Torrecillas (2005) suggested that the selection of discount rates for social projects may be divided into three categories: a zero discount rate, constant discount rates, and time declining discount rates.

A zero discount rate has been proposed by a number of writers. Azar and Sterner (1996) suggested that the rate of pure time preference should be zero, and therefore, a zero discount rate should be used if the economic growth declines when the world economy reaches a certain level. Dasgupta et al. (1999) pointed out that if the production activity of humans contributed to too much of the accumulation of “public bad,” such as GHG emissions, the discount rate could be zero, or even negative. Constant discount rates ranging from 2 to 10% are most commonly used by current government agencies and organizations (Rambaud and Torrecillas, 2005). In addition, in a recent report prepared by Sir Nicholas Stern for the British Government in 2006, the writer proposed a 1.4% discount rate for a 100-year time horizon in relation to GHG abatement strategies. This 1.4% discount rate is computed based on the feasibility and costs of stabilizing GHG concentrations in the atmosphere within a desired range (to less than 550 parts per million) to avoid catastrophic climate change. Time declining discount rates, such as hyperbolic discounting (Henderson and Langford, 1998) and gamma discounting (Weitzman, 2001), have also been proposed. However, these discount rates are not widely used in practice. To the writers’ knowledge, the U.K. government is the first

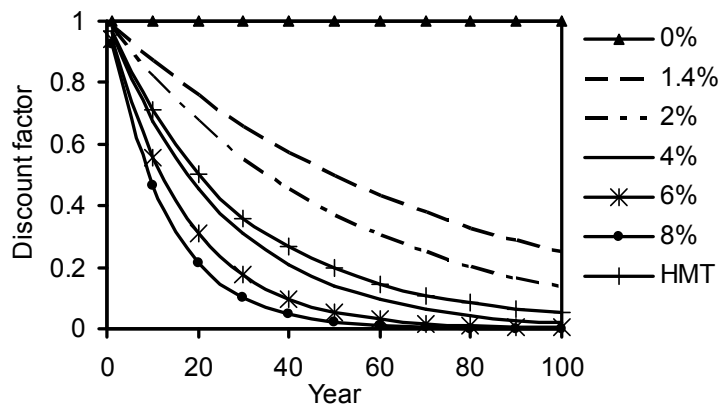


Figure 5.2 Discount rates and their corresponding discount factors over 100 years

government that has adopted a time declining discount rate. In The Green Book (Her Majesty's Treasury, 2003), a long term discount rate is suggested to be 3.5% for periods within 0-30 years, declining to 1.0% at year 300 and held constant thereafter. This time declining discount rate is referred to as the Her Majesty's Treasury (HMT) discount rate in this paper.

In this study, a number of constant discount rates and the HMT time declining discount rate are used in computing the objective function values of WDS optimization to investigate the sensitivity of the optimization results to discount rates. The discount factors calculated from these selected discount rates for up to 100 years are plotted in Figure 5.2. It can be seen that the discount factor computed using a zero discount rate is 1.0 for any time period. This is because a zero discount rate places equal weight on the costs and benefits at present and those in the future. As the discount rate increases, the corresponding discount factor over time declines more quickly. A 1.4% discount rate leads to a discount factor of 0.5 at the 50th year, whereas an 8% discount rate results in near zero discount factors from year 60 onward. The discounting effect of the HMT time declining rate is between the effects of the discount rates of 2 and 4%, but closer to the 4% value.

The selection of discount rates (either a positive discount rate or a zero discount rate) for global warming mitigation is also a complex and controversial issue. Very often, a zero discount rate (or no discounting) is used for GHG impact evaluation. For example, the Intergovernmental Panel on Climate Change (IPCC) has adopted a zero discount rate with a 100-year time horizon for the calculation of GHG emission impacts in its Second Assessment Report [as reported by Fearnside (2002)]. However, if in the future more advanced technology is able to significantly reduce the cost of GHG abatement or carbon sequestration, the discount rate used for GHG impact evaluation could be positive as suggested in Fearnside et al. (2000). As a result, two discount scenarios are considered in this paper. In the first discount scenario, costs are discounted at various discount rates while a zero discount rate is always used for the calculation of GHG emissions as suggested by IPCC. In the second discount scenario, both costs and GHG emissions are discounted at the same rate.

5.3 Problem formulation

The WDS optimization problem investigated in this study is a multiobjective optimization problem that accounts for two objectives: the minimization of total cost and the minimization of GHG emissions. The evaluation of each of these two objectives is presented in the next two subsections, respectively. In this study, only pipe sizing, pump selection, and tank location selection are considered as decision variables to demonstrate the proposed multiobjective optimization for incorporating consideration of GHGs. For a real WDS design problem, many other issues including valve settings and system operation would also need to be taken into account. The equality constraints, which are hydraulic constraints in this study, are accounted for by using the hydraulic simulation model EPANET2. The inequality constraints (for example, minimum allowable pressures at demand nodes), which are design constraints, are handled by using constrained tournament method within the genetic algorithm formulation (Deb, 2000).

5.3.1 Minimization of total cost of WDSs

The total cost of a WDS considered in this study consists of capital costs, pump replacement or refurbishment costs, and operating costs, given by

$$\text{Minimize } f_1 = CC + PRC + OC \quad (5.2)$$

where, CC , PRC and OC are capital costs, pump replacement costs and operating costs, respectively. The capital cost results from the purchase and installation of network components (pipes and pumps) and construction of pump stations. This cost occurs at the beginning of a project. As the service life of a WDS is much longer than the service life of pumps, pumps need to be replaced periodically to ensure the performance of the system is maintained. The operating cost is mainly due to electricity consumption during system operation due to pumping. Both pump replacement costs and operating costs occur during the service life of the system, therefore, the calculation of these two costs requires PVA.

Capital Cost

The capital cost is given as

$$CC = \sum_{i=1}^{npipe} PiC(pipe_i) + \sum_{j=1}^{npump} SC(pump_j) \quad (5.3)$$

where, $npipe$ is the number of pipes; $npump$ is the number of pumps; PiC is the pipe cost, that is a function of pipe diameters (for purchase and installation); and SC is the pump station cost (including the initial purchase of the pumps), which is computed according to the rated power of the corresponding pumps.

Pump Replacement Cost

In this study, a pump service life of 20 years and a system design life of 100 years have been assumed. Therefore, pumps will be replaced or refurbished four times during the design life of the system, and the pump replacement cost is the sum of the PV of the pump costs, as given below

$$PRC = \sum_{j=1}^{npump} PV(PuC(pump_j)) \quad (5.4)$$

where, PuC is the pump cost, which is calculated according to the rated power of the corresponding pump.

Operating Cost

The operating cost is given as

$$OC = PV(AOC) \quad (5.5)$$

where, AOC is the annual operating cost. In Equation 5.5

$$AOC = ET \times AEC \quad (5.6)$$

where, ET is the electricity tariff in dollars per kWh (Australian dollars have been used in this study); AEC is the annual electricity consumption in kWh from the pumping system operation, which can be expressed by the following equation:

$$AEC = \frac{P \times HR}{\eta_{motor}} = \frac{\gamma QH}{\eta_{pump}} \times \frac{HR}{\eta_{motor}} \quad (5.7)$$

where, P is the power of the pump; HR is the annual pumping hours; γ is the specific weight of water; Q is the flow; H is the pumping head; η_{pump} is the pump efficiency; and η_{motor} is the motor efficiency.

In the case study for this paper, the computation of the annual operating cost is taken as the annual operating electricity consumption multiplied by the assumed average electricity tariff. In practice, electricity tariffs may vary considerably across regions and with time. In this study, an electricity tariff of \$0.143 per kilowatt-hour (kWh) has been assumed. This cost is an approximate average electricity cost of peak and off-peak electricity. A motor efficiency of 95% for each pump has been assumed in the computation of the annual energy consumption. In practice, the demand varies with time and therefore, an extended period simulation should be used to compute a more accurate estimate of the annual electricity consumption over the years. This will more correctly account for seasonal demand variation, the correct split between peak and off-peak pumping, the fluctuation in tank levels, and variation of pump operating point during the day. A more accurate estimate of the annual operating cost would then be obtained. In this study, a single design flow and a constant demand are used to demonstrate the proposed multiobjective methodology. Therefore, the system is designed for an assumed peak demand for the beginning of the design period, which is then assumed to not change over the design life of the project.

5.3.2 Minimization of GHG emissions of WDSs

The total GHG emissions considered in this study consist of capital and operating emissions, given by

$$\text{Minimize } f_2 = CGHG + OGHG \quad (5.8)$$

where, $CGHG$ (as defined in Equation 5.9) and $OGHG$ (as defined in Equation 5.10) are the capital and operating GHG emissions, respectively. Capital emissions are due to the manufacture and installation of network components, such as pipes, pumps, valves and tanks. In this study, only pipes are considered as the source of capital emissions. These emissions occur at the beginning of a project. Similarly to the operating costs, operating emissions

are due to electricity consumption related to the operation of the system over time. Therefore, the calculation of operating emissions also requires PVA.

Capital GHG Emissions

The capital emissions can be calculated using the following equation:

$$CGHG = EF \times \sum_{i=1}^{npipe} EE(pipe_i) \quad (5.9)$$

where, EF is the emission factor; and EE is the embodied energy of pipes. Embodied energy is all of the energy required to manufacture a specific product (Treloar, 1994). Once the embodied energy of pipes is determined, the emission factor is used to convert the energy into actual GHG emissions in kilogram (kg).

In practice, the embodied energy values and emission factors may also vary across regions and with time, depending on the material excavation and extraction methods used and the makeup of electricity energy sources (for example, thermal, nuclear, wind, hydroelectricity, etc.). In this study, a specific value of the embodied energy for ductile iron cement mortar lined (DICL) pipes of 40.2 MJ/kg is used. This value was estimated by Ambrose et al. (2002) based on a combination of published data and actual factory manufacturing data. It should be noted that the values of embodied energy in megajoule/kilogram (MJ/kg) need to be interpreted carefully, as different types of pipes have different wall thicknesses and different densities, and therefore need different amounts of material per meter length of pipe to manufacture (Ambrose et al., 2002). Thus, before the embodied energy value in MJ/kg can be used in piping system energy analysis, it needs to be translated into units of megajoule/meter (MJ/m) length by multiplying it by the unit mass [in kilogram/ meter (kg/m)] of the pipes. A constant emission factor of 1.042-kg carbon dioxide equivalent (CO₂-e) per kilowatt-hour (kWh) has been used in this paper. This value is a full fuel cycle emission factor for end electricity users in South Australia (Australian Greenhouse Office, 2006). Clearly, this value is an estimate and any analysis should include a sensitivity

of the results to a lower or higher value and also the possibility that this value will change with time as a different mix of electricity energy sources evolves into the future due to responses by Governments to global warming.

Operating GHG Emissions

The operating emissions are given as

$$OGHG = PV(AOGHG) \quad (5.10)$$

where, $AOGHG$ are the annual operating GHG emissions, which can be calculated by

$$AOGHG = EF \times AEC \quad (5.11)$$

where, EF is the emission factor; and AEC is the annual electricity consumption in kWh.

In this study, the design of WDSs is formulated as a multiobjective optimization problem, in which both the costs and GHG emissions from WDSs are minimized. The outcome of the optimization is a set of non-dominated optimal solutions that apply for the assumptions made for the data used in the study. In a real design setting, it would be important to assess the sensitivity and robustness of the set of non-dominated solutions along the optimal front to changes in data assumptions. Two of the more important data assumptions that should be tested during the sensitivity analysis include the embodied energy factor and emission factor. However, such an analysis is beyond the scope of this paper.

5.4 Case study

5.4.1 Case study description

For the case study, water needs to be delivered from a water source with an elevation of EL.0.0 to a small town with an elevation of around EL.110 m (Figure 5.3) via two possible tanks. The network consists of a transmission network and a distribution network. The transmission network consists of a fixed speed main pump, a rising main, a fixed speed booster pump, a transmission main, and a storage tank. The distribution network consists of a distribution main, a four-pipe network and four nodes. There are two possible tank locations and only one location will be selected. Location one (Node 10) is on the top of a hill (EL.190 m) and location two (Node 11) is on the side of the hill (EL.140 m). Location one is higher, which requires more energy to pump water into the tank; however, it is closer to the town and the higher elevation gives it an advantage in distributing water into the downstream network where smaller pipes should be required. Location two is lower in elevation, but is further away from the town (Table 5.1). The system needs to be able to deliver at least 80 L/s water at three demand nodes (Nodes 6–8) in the town during the peak hour (thus a total demand of 240 L/s from the tank). Therefore, the transmission network needs to be able to deliver at least 120 L/s of water to the tank on the peak day (a peak hour factor of 2 has been assumed) (Water Services Association of Australia, 2002). The pressure heads at the demand nodes need to be higher than 20 m to provide adequate pressure to residents to perform daily activities. A simplified network has been studied here to demonstrate the framework for considering the tradeoffs between costs and GHG emissions. For more realistic applications, other complexities involved in water distribution designs, such as staging and additional demand loading cases (e.g., fire demand loading cases and reliability breakage loading cases), could also be considered. However, it would be straightforward to add these considerations into the simulation runs carried out during the

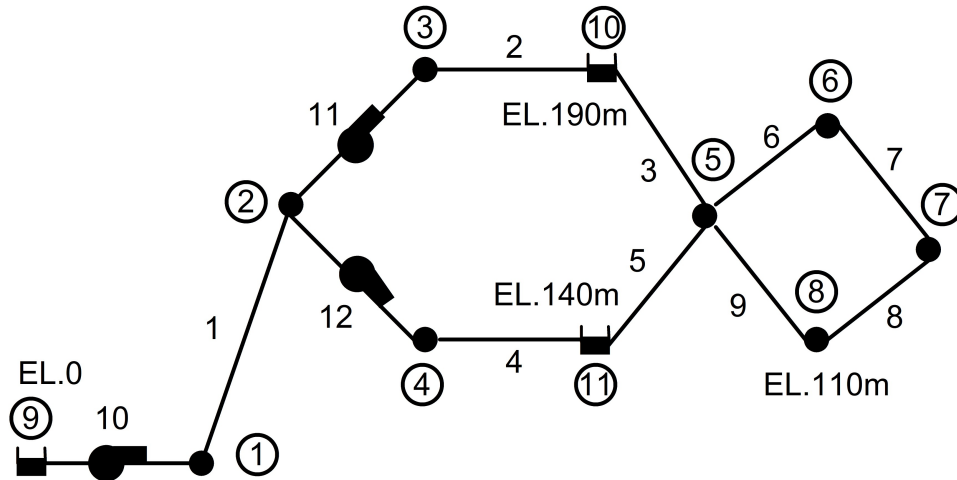


Figure 5.3 Case study network configuration

Table 5.1 Pipe lengths for the case study network

Pipe	Length (m)
1	10,000
2	10,000
3	10,000
4	10,000
5	13,000
6	2,000
7	3,000
8	2,000
9	3,000

multiobjective optimization analysis. This is one of the advantages of using genetic algorithm analysis, where simulation is an independent component of the optimization process, enabling changes in the system to be accommodated easily.

In this case study, the available options for the decision variables include 30 pump curves for 16 different fixed speed pumps selected using Thompson Kelly and Lewis' pump selection computer program EPSILON and 16 ductile iron cement mortar lined (DICL) pipes of different diameters. Details of the pumps and pipes are given in Tables 5.2 and 5.3, respectively. The WSMGA described previously is used to optimize the system for both discount scenarios. Keedwell and Khu (2006) pointed out that the starting position in the search space is important for genetic algorithms to find desired solutions in multiobjective optimization. Consequently, 100 random seeds (i.e., random starting positions) have been used in this paper to ensure near-globally optimum solutions are found.

The optimization results obtained from Discount Scenarios 1 and 2 are presented in the next two subsections, respectively. The results presented are the best values obtained from the 100 runs with different random starting positions. There were some variations in the optimal fronts obtained when different random seeds were used, but as the objective of this paper is to explore the optimal tradeoffs between economic and environmental objectives, the best results from each of these runs have been combined into a single front. The fact that the algorithm converged to different fronts is likely to be due to the size and complexity of the discrete search space and highlights the increased level of complexity when multiobjective optimization problems are considered.

Table 5.2 Pump information for the case study network

No.	Pump type	Speed (rpm)	Impeller dia. (mm)	BEP* (%)	Q at BEP (L/s)	H at BEP (m)	Rated Power (kW)	Station cost (10 ³ \$)	Pump cost (10 ³ \$)
1A	8*17A_ECS-2s	1475	410	83	126	107	159	990	644
1B	8*17A_ECS-2s	1475	432	83	130	120	183	1,086	723
2A	8*17B-3s	1475	393	82	112	118	158	988	643
2B	8*17B-3s	1475	445	84	130	154	233	1,263	875
3A	8*17B_ECS-2s	1475	445	84	130	104	158	985	640
4A	8HN124A	2950	293	79	175	95.9	209	1,181	803
4B	8HN124A	2950	318	81	189	119	272	1,384	985
5A	6LG13/A	2900	311	80	109	117	155	975	633
5B	6LG13/A	2900	321	81	113	125	171	1,039	684
6A	430DMH-4s	1480	275	84	157	94.6	173	1,047	690
6B	430DMH-4s	1480	312	85	180	121	251	1,320	926
7A	430DMH-5s	1480	251	84	142	99.2	164	1,011	662
7B	430DMH-5s	1480	312	85	180	151	313	1,502	1,097
8A	430DML-5s	1480	290	82	131	101	159	989	644
8B	430DML-5s	1480	313	82	140	118	197	1,138	767
9A	430DML-6s	1480	272	81	123	107	158	988	643
9B	430DML-6s	1480	313	82	140	142	238	1,277	888
10A	460CDKH-4s	1480	280	81	183	93.5	206	1,169	793
10B	460CDKH-4s	1480	336	83	220	134	348	1,593	1,187
11A	460DKL-3s	1480	334	85	182	87	182	1,081	719
12A	460DKL-4s	1480	295	84	162	90.7	171	1,038	683
12B	460DKL-4s	1480	336	85	185	116	247	1,306	914
13A	510DML-3s	1480	332	80	220	83.4	226	1,238	853
13B	510DML-3s	1480	369	81	240	104	301	1,469	1,065
14A	510DMH-6s	980	339	83	197	88.3	204	1,164	788
14B	510DMH-6s	980	368	83	215	103	261	1,350	954
15A	200*300-630	1480	537	81	192	97.1	224	1,233	849
15B	200*300-630	1480	635	83	230	135	367	1,641	1,235
16A	250*300-500B	1480	553	84	273	93.9	298	1,461	1,057
16B	250*300-500B	1480	562	84	275	97.3	311	1,496	1,091

*BEP: Best efficiency point

Table 5.3 Ductile iron cement mortar lined (DICL) pipe information for the case study network

No.	Dia. (mm)	Unit Cost (\$/m)	Unit Mass (kg/m)	No.	Dia. (mm)	Unit Cost (\$/m)	Unit Mass (kg/m)
1	100	228	18	9	675	1,658	213
2	150	307	30	10	700	1,739	223
3	225	433	51	11	750	1,900	244
4	300	568	74	12	800	1,950	266
5	375	813	99	13	825	1,976	277
6	450	1,033	126	14	900	2,012	310
7	525	1,252	154	15	960	2,040	337
8	600	1,415	183	16	1000	2,142	356

5.4.2 Optimization results from discount scenario 1 (GHGs always discounted at zero rate)

All of the Pareto-optimal fronts obtained from the first discount scenario using different discount rates for costs [zero, 1.4%, 2%, 4%, 6%, 8%, and declining (HMT)] are plotted in Figure 5.4. In this discount scenario, both high tank solutions and low tank solutions (contained in the ovals in Figure 5.4) are found on the optimal front, no matter which discount rate is used. In general, high tank solutions have lower cost but have higher GHG emissions compared to low tank solutions. It is evident from the figure that the discount rate used has a significant impact on the optimal front. As the discount rate for costs increases, the optimal fronts switch toward the left on the graphs in Figure 5.4. This is because when a high discount rate is used, the future costs (including operating costs and pump replacement costs) are heavily discounted, which results in lower total costs.

However, compared to the total costs of the optimal solutions, the total GHG emissions generated from the networks, especially low tank networks, are less sensitive to the discount rate used for calculating ongoing costs. GHG emissions generated from all low tank solutions are within a similar range (220–240 kt), as most of the constant discount rates for costs (from 0 to 6%)

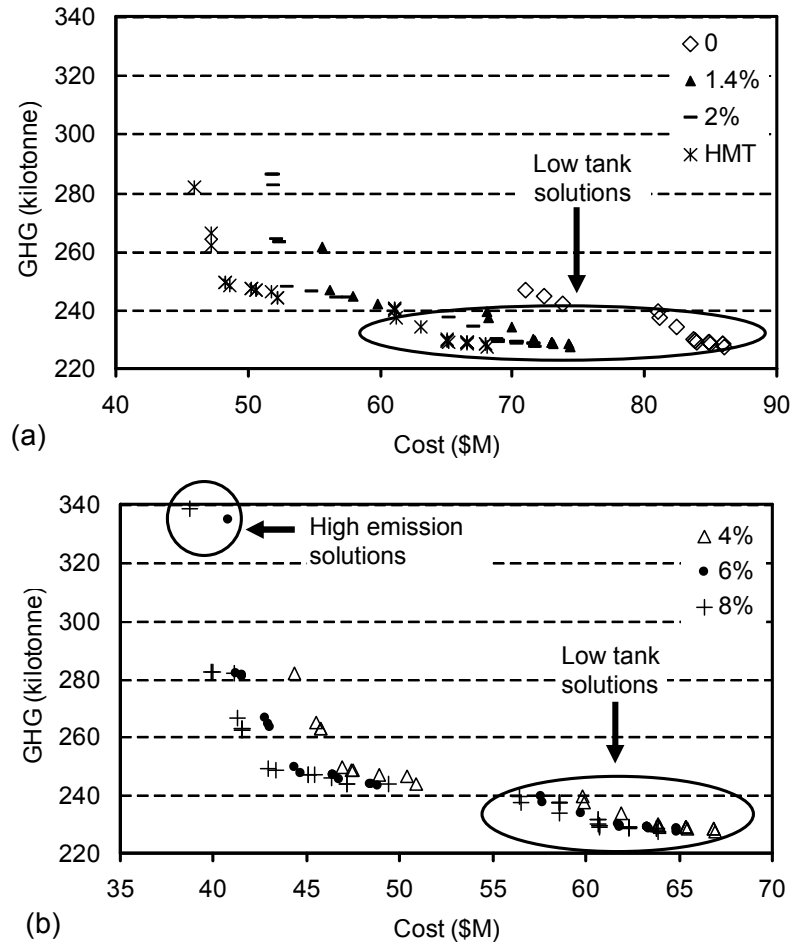


Figure 5.4 Optimization results from discount scenario 1 (GHG emissions not discounted): (a) Optimal fronts obtained using discount rates of zero, 1.4%, 2% and the HMT time declining discount rate; (b) Optimal fronts obtained using discount rates of 4%, 6% and 8%

lead to the same set of low tank solutions on the optimal fronts. Whereas for high tank solutions, when the discount rate is increased to a certain level, in this case 6% and higher, networks with extremely high emissions [solutions contained in the circle in Figure 5.4(b)] are introduced into the optimal front due to their low costs.

The optimization results obtained in this discount scenario also show that the inclusion of GHG emission minimization as one of the objectives results in significant tradeoffs between the economic and environmental objectives. The tradeoffs obtained using the discount rates of 1.4 and 6% are presented in Figures 5.5(a) and 5.5(b), respectively. These tradeoffs provide decision makers with an improved understanding of the objective space. When a discount rate of 1.4% is used, 19 solutions (four high tank solutions and 15 low tank solutions) are found along the optimal front. When a discount rate of 6% is used, 30 solutions (15 high tank solutions and 15 lower tank solutions) are found on the optimal front. The network configurations of a number of typical solutions for each discount rate are provided in Table 5.4. The last column of Table 5.4 shows the percentage of operating energy that is used to overcome friction losses in the corresponding networks. The costs and emissions from these solutions are summarized in Table 5.5.

Table 5.5 and Figure 5.5(a) show that when a discount rate of 1.4% is used, from the lowest cost solution (Design A) to the second lowest cost solution (Design B), a \$0.6 million increase in cost results in a 15-kt reduction in GHG emissions. This is equivalent to \$40/t of GHGs in the form of CO₂-e [Figure 5.5(a)]. However, from Design B to Design C (the lowest emission high tank solution), the cost of reducing 1 t of GHGs is increased to \$720/t CO₂-e. The low tank solutions, such as Designs D (the lowest cost low tank solution) and E (the lowest emission low tank solution) generate fewer GHG emissions compared to the high tank solutions. However, these low tank solutions are much more expensive, which also lead to higher costs for reducing every tonne of GHG emissions. The tradeoffs between the two objectives can vary when different discount rates are used. When a discount rate of 6% is used, Table 5.5 and Figure 5.5(b) show that from the lowest cost solutions (Design

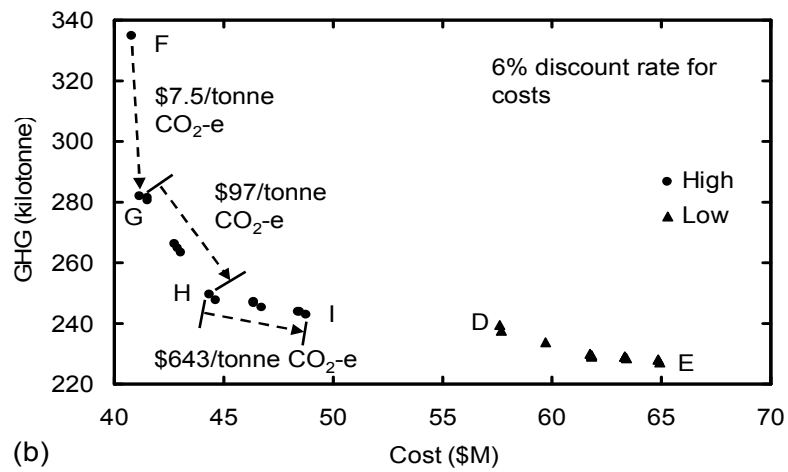
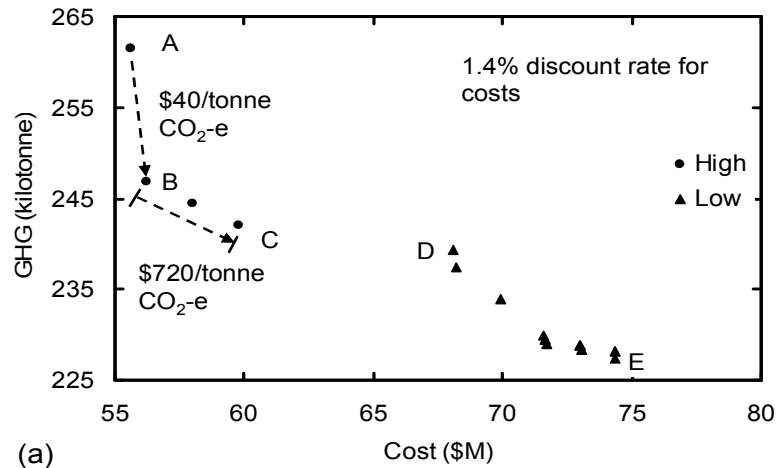


Figure 5.5 (a) Optimal solutions obtained using the discount rate of 1.4%; (b) optimal solutions obtained using the discount rate of 6%

Table 5.4 Network configurations and characteristics of solutions obtained in discount scenario 1

Discount rate	No.	Pump No.1 and No.2	Pump No.1 and No.2 efficiency	TL*	Pipe Diameter (mm)									Flow (L/s)	Annual Operating Hours
					1	2/4	3/5	6	7	8	9				
1.40%	A	3A, 1B	83%, 82%	High	375	450	450	300	150	300	450	121	5,812		
	B	3A, 3A	83%, 83%	High	450	450	450	300	150	300	450	123	5,682		
	C	3A, 3A	84%, 84%	High	525	525	450	300	150	300	450	133	5,252		
	D	3A, 3A	81%, 81%	Low	450	450	675	450	100	450	600	151	4,638		
	E	11A, 11A	83%, 83%	Low	600	600	675	450	100	450	600	201	3,478		
6%	F	2B, 2B	83%, 83%	High	375	300	450	600	300	100	300	123	5,716		
	G	2B, 8A	84%, 81%	High	375	375	450	300	150	300	450	128	5,478		
	H	3A, 8A	83%, 81%	High	450	450	450	300	150	300	450	123	5,701		
	I	3A, 3A	84%, 84%	High	525	525	450	300	100	300	300	133	5,252		
	D	3A, 3A	81%, 81%	Low	450	450	675	450	100	450	600	151	4,638		
	E	11A, 11A	83%, 83%	Low	600	600	675	450	100	450	600	201	3,478		

Table 5.5. Different components of objective function values of solutions obtained in discount scenario 1

Discount rate	No.	Capital cost (M\$)	Pump replacement cost (M\$)	Annual operating cost (M\$)	Operating cost over 100 years	Total cost (M\$)	Capital GHG (kt)	Annual operating GHG (kt)	Operating GHG over 100 years (kt)	Total GHG (kt)
1.40%	A	37.2	2.85	0.29	15.6	55.6	49.6	2.12	212	262
	B	39.3	2.68	0.27	14.3	56.2	52.7	1.94	194	247
	C	43.6	2.68	0.25	13.5	59.8	59.2	1.83	183	242
	D	53.2	2.68	0.23	12.1	68.1	74.3	1.65	165	239
	E	61.1	3.01	0.19	10.3	74.4	87.6	1.40	140	227
6%	F	33.4	0.79	0.40	6.62	40.8	44.6	2.90	290	335
	G	35.1	0.68	0.32	5.37	41.2	46.6	2.35	235	282
	H	39.3	0.58	0.27	4.49	44.3	52.7	1.97	197	250
	I	44.0	0.57	0.25	4.17	48.8	60.2	1.83	183	243
	D	53.2	0.57	0.23	3.76	57.6	74.3	1.65	165	239
	E	61.1	0.65	0.19	3.19	64.9	87.6	1.40	140	227

F) to the second lowest cost solutions (Design G), a \$0.4 million increase in cost leads to a 53-kt decrease in GHG emissions, which equals to only \$7.5/t of CO₂-e [Figure 5.5(b)]. However, from Design G to Design H, the cost to reduce 1 t of GHGs is increased to \$97/t of CO₂-e. From Design H to the lowest cost high tank solution (Design I), the cost is further increased to \$643/t of CO₂-e.

As the discount rate used has a significant impact on the tradeoffs between the two objectives, the use of different discount rates can lead to different final solutions. For example, Design B in Figure 5.5(a) and Design G in Figure 5.5(b) provide reasonable tradeoffs between total cost and GHG emissions, as they correspond to the break points in the objective space where the marginal returns are diminishing. Tables 5.4 and 5.5 show that they are different solutions. The capital cost of Design G is \$4.2 million lower compared to Design B due to the smaller pipes selected for the upstream network. However, the annual operating cost and emissions of Design B are much lower, which lead to 35 kt less GHGs generated over 100 years compared with Design G.

5.4.3 Optimization results from discount scenario 2 (costs and GHGs discounted at the same rate)

The optimal fronts obtained from Discount Scenario 2 are plotted in Figure 5.6. Similar results have been found for this discount scenario as for Discount Scenario 1 in that the inclusion of GHG emission minimization as one objective results in significant tradeoffs between the two objectives. Figure 5.6 shows that in all of the optimal fronts found using different discount rates, the total costs increase as the GHG emissions decrease, as expected.

The discount rate used also has a significant impact on the optimization results obtained in this discount scenario. Apart from the impact of the discount rates described in the preceding section, the impact of discount rates in this scenario manifests itself in two other ways. First of all, as the discount

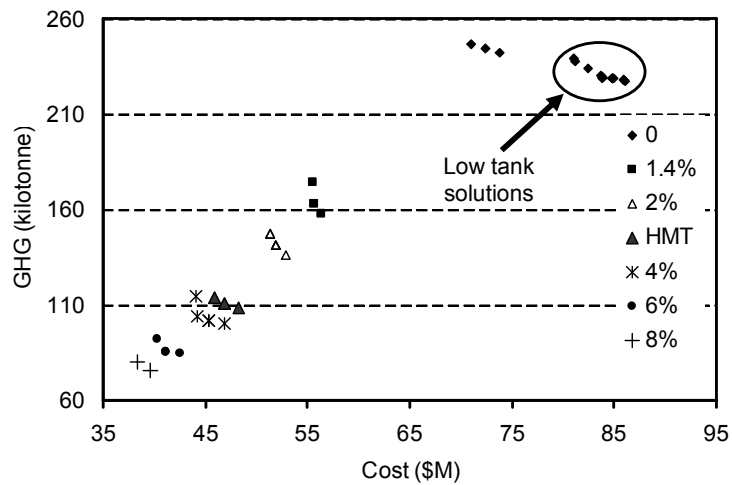


Figure 5.6 Optimization results from Scenario 2 (both costs and GHGs discounted)

rate used increases, the number of solutions on the optimal front decreases. When a zero discount rate is used for both costs and GHGs, there are 18 solutions on the optimal front. They include the lowest cost solution, the lowest emission solution, and 16 solutions in between. However, when the discount rate is increased to 8%, only two extreme solutions remain on the front. This is because a high discount rate discounts both the future cost and emissions heavily in this discount scenario. As a result, the capital components dominate both objective function values and the tradeoffs between the two objectives are reduced.

Second, the discount rate used has an impact on the tank location that is selected. When a zero discount rate is used, both high and low tank solutions are found on the optimal front. However, once both the future costs and emissions are discounted, the low tank solutions disappear from the optimal front. This can be explained by comparing the components of objective function values of high and low tank solutions. Figure 5.7 shows the different components of the objective function values of the optimal solutions obtained

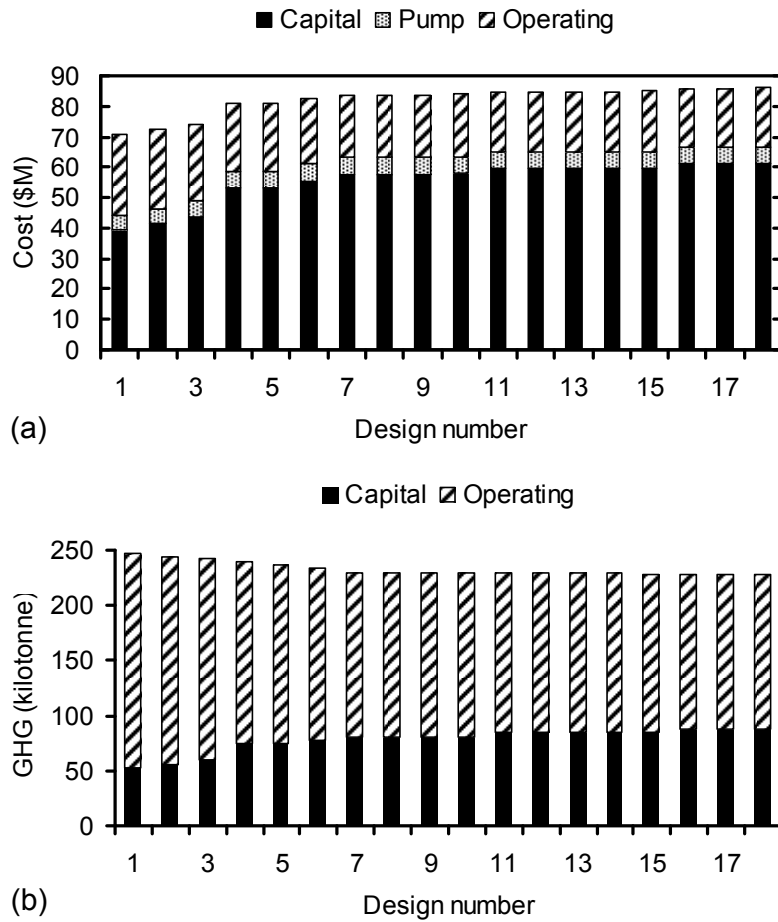


Figure 5.7 (a) Composition of total costs; (b) Composition of total GHG emissions (Design 1 and Design 18 are the minimum cost and minimum GHG emission solutions obtained using a zero discount rate in discount scenario 2, respectively)

by using a zero discount rate. Solution 1 is the lowest cost solution and Solution 18 is the highest cost solution. Solutions 1-3 are high tank solutions and the rest are low tank solutions. It is evident that capital costs make the biggest contribution to the total costs. High tank solutions have a lower total cost, mainly due to their lower capital costs. In contrast, operating emissions make the biggest contribution to the total emissions. As a result, lower tank solutions have lower total emissions due to their lower operating emissions.

It is important to note that the use of a high discount rate in Discount Scenario 2 is extremely beneficial to the high tank location. In general, the use of higher discount rates increases the impact that capital costs and capital emissions have on the total costs and total GHG emissions by reducing the weighting given to the future costs and emissions. Thus, the disadvantage of the high tank location of having higher operating costs and emissions is reduced by the use of higher discount rates. In addition, the high tank location has an advantage over the low tank location in that Pipe 3 is 3 km shorter than Pipe 5 and hence will lead to a lower capital cost. Also, the higher elevation allows the high tank to reduce the capital cost by reducing the pipe sizes in the downstream distribution network. Therefore, the high tank location is more likely to be selected when higher discount rates are used.

5.5 Summary and conclusions

In this paper, a multiobjective approach has been used for optimizing the design of WDSs. In addition to the traditional economic objective (minimization of total life cycle cost), an environmental objective (minimization of GHG emissions) has been taken into account. The results for the case study show that the inclusion of GHG emission minimization as one objective results in significant tradeoffs in the form of a Pareto-optimal front between the economic and environmental objectives. Often, an increase in cost that is deemed reasonable and acceptable can result in a substantial reduction in GHG emissions. The case study shows that the cost to reduce

GHG emissions can be as low as \$7.5/t of CO₂-e. In addition, a significant advantage of multiobjective optimization over single-objective optimization is that the multiobjective optimization results can be presented as a Pareto-optimal front. On the Pareto-optimal front, the points of diminishing marginal returns are clearly evident, where a large increase in cost only produces a relatively small decrease in GHGs. The Pareto-optimal front significantly improves the designer's understanding of the search space and shows which design gives the biggest "bang for the buck" in reducing GHGs.

In this study, time preference has been taken into account by using PVA in the objective function evaluation process. As there is controversy as to which discount rate should be used in PVA for mitigating climate change, various discount rates were used to explore the impact that discount rates have on the optimization results. The optimization results show that different discount rates result in different tradeoffs and thus, different final designs of WDSs. In Discount Scenario 1 (GHG emissions not discounted), both high tank solutions and low tank solutions are selected. A higher discount rate can lead to solutions with smaller pipes in the upstream network due to increased impact of capital cost on the total cost. In the second discount scenario (both costs and emissions discounted), higher discount rates are more likely to result in solutions with the high tank location. This is because higher discount rates reduce the impact the system has on the future, in this case the pump replacement costs, operating costs, and operating emissions, in the PV calculations. Consequently, solutions with lower capital cost and higher operating emissions, in this case the solutions with the higher tank location, are more likely to be selected.

In conclusion, this study has investigated the multiobjective tradeoffs between the cost and GHG emissions from WDSs and has explored the sensitivity of the multiobjective optimization results to the discount rates used. In this study, a simply hypothetical case study has been used. Based on the tradeoffs obtained from the simple network, the framework to evaluate GHG emissions from WDSs, which have been developed in this paper, can now be tested on larger and more realistic WDSs. In addition, since the results in this paper are

based on a number of assumptions, a sensitivity study incorporating the uncertainties of the parameters, such as emission factors and embodied energy factors, into the optimization could be a future research direction. Optimization is used in this paper as an explorative tool to investigate new innovative solutions to a problem with increased complexity due to the consideration of GHG emissions. Engineering judgment is still necessary in making the decision about which network is finally selected.

5.6 Acknowledgments

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Chapter 6

Single-Objective versus Multi-Objective Optimization of Water Distribution Systems Accounting for Greenhouse Gas Emissions by Carbon Pricing

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Wu, W. (Candidate)

Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.

I hereby certify that the statement of contribution is accurate.

Signed:Date:

Maier, H.R.

Research supervision and manuscript evaluation.

I hereby certify that the statement of contribution is accurate and I give permission for the inclusion of the paper in the thesis.

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Research supervision and manuscript evaluation.

I hereby certify that the statement of contribution is accurate and I give permission for the inclusion of the paper in the thesis.

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Abstract

Previous research has demonstrated that there are significant tradeoffs between the competing objectives of minimizing costs and Greenhouse Gas (GHG) emissions for water distribution system (WDS) optimization. However, upon introduction of an emissions trading scheme, GHG emissions are likely to be priced at a particular level. Thus, a monetary value can be assigned to GHG emissions, enabling a single-objective optimization approach to be used. This raises the question of whether the introduction of carbon pricing under an emissions trading scheme will make the use of a multi-objective optimization approach obsolete or whether such an approach can provide additional insights that are useful in a decision-making context. In this paper, the above questions are explored via two case studies. The optimization results obtained for the two case studies using both single-objective and multi-objective approaches are analyzed. The analyses show that the single-objective approach results in a loss of tradeoff information between the two objectives. In contrast, the multi-objective approach provides decision makers with more insight into the tradeoffs between the two objectives. As a result, a multi-objective approach is recommended for the optimization of WDSs accounting for GHG emissions when considering carbon pricing.

6.1 Introduction

Climate change, especially global warming caused by human activities, presents serious global risks. Mitigating global warming by reducing greenhouse gas (GHG) emissions is a unique challenge facing our generation. In order to tackle this challenge, many measures, including emissions/carbon trading schemes, are being introduced. An emissions trading scheme can be implemented in many ways, amongst which, a cap and trade approach is a popular method. Under a cap and trade scheme, emitters of GHGs need to acquire a permit for every tonne of GHG they emit. These permits can be bought and sold on a market. Some businesses may need to buy permits to cover the GHGs they emit; while others may be able to sell any excess permits they own, if they can reduce their emissions by employing advanced technology, for example. As a result, many industries, including the water industry, will be affected by the price of carbon and the amount of GHGs they emit. This leads to a need to incorporate GHG emission considerations into the optimal design and operation of water distribution systems (WDSs).

GHG related issues, such as energy consumption, have been investigated in many studies in WDS research. In the area of optimization, Sarbu and Borza (1998) investigated various solutions to increasing the power efficiency of pumping systems. Baran et al. (2005), Lopez-Ibáñez et al. (2005) and Ulanicki et al. (2007) optimized the scheduling of pumps to reduce electricity costs. In the planning and management area, Lundie et al. (2004) developed a life cycle assessment approach for metropolitan water system planning, in which energy use and direct gaseous emissions are identified as two of the important environmental indicators of a sustainable metropolitan water systems. Filion et al. (2004) also employed a life cycle approach to quantify energy expenditures of pipes in a WDS. More recently, Filion (2008) explored the connections between the urban form and energy use of water distribution networks. In a study carried out by Dandy et al. (2006), GHG emissions resulting from pipe manufacturing were evaluated for a WDS. Following the Dandy study, Wu et al. (2010b) considered the impact of GHG emissions on

the optimal design of WDSs explicitly, by incorporating the minimization of life cycle GHG emissions, together with the minimization of system costs, into the optimal design of WDSs via a multi-objective approach. It is now becoming increasingly common for carbon related emissions to be priced under an emissions trading scheme, yet the impact of carbon pricing on the optimal design and operation of WDSs has not been investigated thus far.

The present study aims to consider the inclusion of carbon pricing into both single-objective and multi-objective optimization approaches for WDS optimization. Wu et al. (2010) demonstrated that there are significant tradeoffs between the competing objectives of minimizing costs and GHG emissions. However, upon introduction of an emissions trading scheme with a cap and trade approach, a monetary value (referred to as the carbon price in this paper) is usually assigned to GHG emissions. This monetary value of the carbon price can be determined by either evaluation methods, as done by the International Panel on Climate Change (IPCC), or a carbon market. The expression of GHG emissions in monetary terms enables a single-objective optimization approach to be used. This raises the question of whether the introduction of carbon pricing under a possible emissions trading scheme will make use of a multi-objective optimization approach obsolete or whether such an approach can provide additional insights that are useful in a decision-making context. In this paper, two case studies were used to compare single and multi-objective approaches when considering both cost and carbon emission objectives. Based on the results obtained for the case studies, recommendations regarding the optimization of WDSs under a carbon pricing regime as determined by an emissions trading scheme are presented.

The remainder of the paper is organized as follows. The methods used to solve the proposed WDS optimization problem, including evaluation of the objective functions, the optimization approach adopted, carbon pricing and present value analysis, are introduced in the next section. Next, the two case studies are introduced, to which both single-objective and multi-objective optimization approaches are applied. Thereafter, the optimization results

obtained using the two approaches are presented and discussed. Finally, conclusions and recommendations are presented.

6.2 Methods

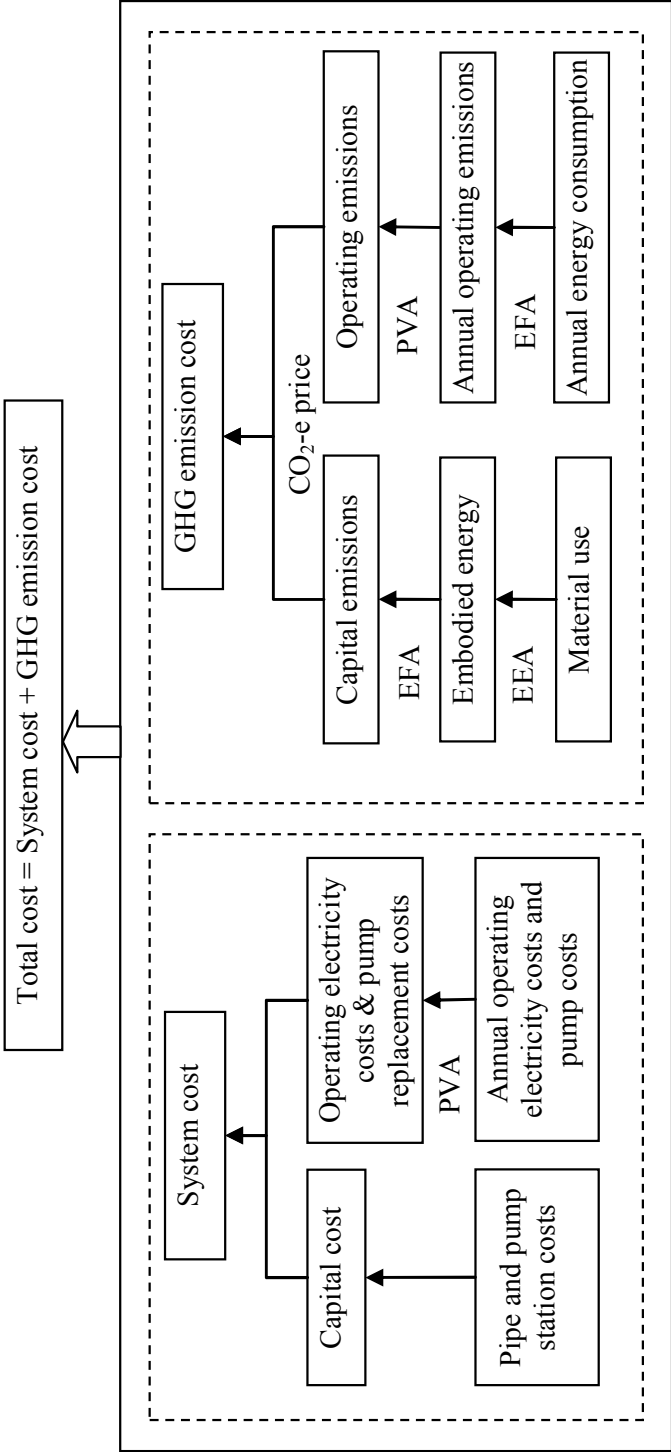
6.2.1 Objective function evaluation

The WDS optimization problem investigated in this paper is a multi-objective optimization problem that accounts for two objectives: the minimization of system costs and the minimization of GHG emissions (via a price for carbon). When the single-objective optimization approach is used, the total cost, which is the sum of the system costs and the GHG costs expressed in terms of dollars for the cost of carbon related emissions, is minimized as the sole objective. In contrast, in the multi-objective approach, the system and GHG costs are minimized as two separate objectives.

Figure 6.1 shows the objective function evaluation process. The system cost considered in this study is defined as the sum of the capital costs, operating costs for pumping and pump replacement/refurbishment costs at regular intervals during the service or design life of the system. The capital cost is incurred due to the purchase and installation of network components (pipes and pumps) and construction of pump stations. This cost occurs at the beginning of a project. As the design life of a WDS is much longer than the service life of pumps, then pumps and electrical control equipment need to be replaced or refurbished periodically to ensure the performance of the system is maintained. In the case studies in this paper, a 100-year pipe network service life and a 20-year pump service life are assumed. The operating cost is incurred mainly due to the system operation of pumping. The computation of the annual operating cost is taken as the annual energy consumption multiplied by an average electricity tariff. A motor efficiency of 95% is assumed for each pump. In practice, electricity tariffs may vary across regions

and with time. In this study, an electricity cost of 0.143 dollars per kWh is assumed, which is an approximate average electricity tariff taking into account peak and off-peak tariffs. As both pump replacement/refurbishment costs and operating electricity costs occur during the life of the system, calculation of these two costs requires present value analysis.

In calculating the annual energy consumption, a 48-hour extended period simulation (EPS) has been used in the simulation model to account for the diurnal variation in demand, the fluctuation in tank water levels and the variation of the pump operating point during the day, to provide a realistic estimate of the operational behavior of the system. In the EPS, a diurnal demand curve presented in Figure 6.2 applied to the average flow during a year or the average-day flow (Water Services Association of Australia, 2002) is used to estimate the average energy consumption of the system due to pumping during the design period (100 years). In addition, an average flow on the peak day is used to design the distribution systems upstream of the balancing storage tanks, as suggested by Water Services Association of Australia (2002). The average flow on the peak day is computed by multiplying the average-day flow by the Peak Day Factor (PDF). In this paper, a PDF of 1.5 obtained from the Water Services Association of Australia (2002) is used. It should be noted that in designing distribution systems downstream of the balancing storage tanks, the average flow on the peak hour and fire loading cases would also be required to ensure an adequate design. In both case studies, an average pipe roughness value of $\epsilon=0.25\text{mm}$ was assumed for the first 50-year period and a value of $\epsilon=1.5\text{mm}$ for the second 50-year period in order to account for pipe aging.



Note: PVA = present value analysis; EFA = emission factor analysis; EEA = embodied energy analysis

Figure 6.1 Objective function evaluation

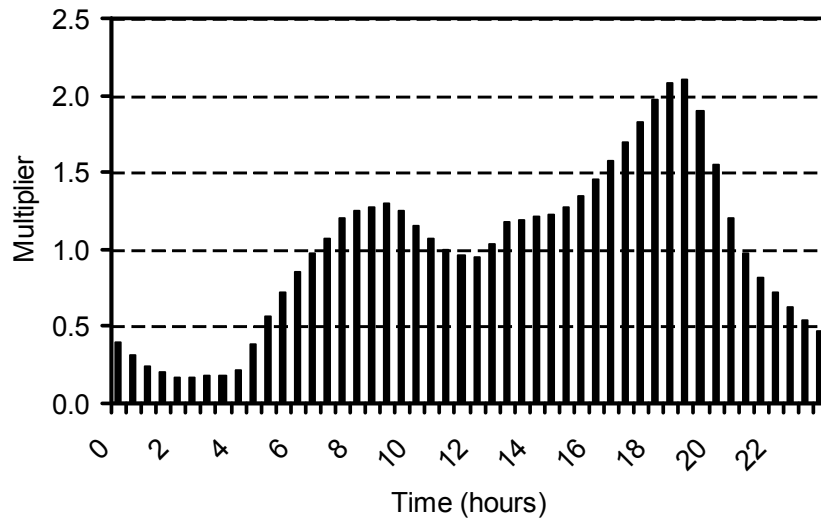


Figure 6.2 Diurnal water demand curve (Hydraulic Computer Programming Pty. Ltd, 1985)

GHG emission costs are obtained by multiplying the carbon price by the total GHG emissions of the system. The total GHG emissions considered in this study consist of capital emissions and operating emissions. Capital emissions are due to the manufacture and installation of network components, such as pipes, pumps, valves and tanks. In this study, pipes are the only source of capital emissions considered, as they represent the largest proportion of the impact (Filion et al., 2004). These emissions occur at the beginning of a project. Similarly to the operating cost, operating GHG emissions are due to electricity consumption related to the operation of the system over time in regions where it is assumed that fossil fuels are used for electricity generation. Operating emissions occur over time during the service life of the system. Therefore, the estimation of total operating emissions over the service life of the network also requires present value analysis.

In addition, in evaluating the capital emission costs, embodied energy analysis (EEA) is first applied to translate the material use of the pipes into an estimate

of their embodied energy in MJ. Thereafter, emission factor analysis (EFA) is used to translate embodied energy use into a corresponding estimate of GHG emissions in kg of CO₂-e (carbon dioxide equivalent). In practice, embodied energy values and emission factors may also vary across regions and with time, depending on the material excavation and extraction methods used and the makeup of electricity energy sources (for example, thermal, nuclear, wind, hydroelectric, etc.). In this study, a typical embodied energy of ductile iron cement mortar lined (DICL) pipes of 40.2 MJ/kg and a typical emission factor of 1.042 kg CO₂-e per kWh are used. The embodied energy value of DICL pipes has been obtained from Ambrose et al. (2002), and the emission factor selected is a full fuel cycle emission factor for end electricity users in South Australia (Australian Greenhouse Office, 2006). While the embodied energy and emission factor values are realistic estimates, and adequate for the purpose of this paper, they are likely to change with time in actual applications due to changes in the way electricity is being generated as governments respond to the threat of climate change (e.g. an increase in wind power generation to replace production from coal-fired power stations).

6.2.2 Optimization approach

In this paper, a multi-objective genetic algorithm (GA) is used, as GAs have been shown to be effective for WDS optimization problems (Simpson et al., 1994). GAs are a global optimization method that belong to the class of evolutionary algorithms (Goldberg, 1989). GAs differ from traditional optimization techniques in that the concept of GAs is inspired by natural phenomena of heredity. GAs use the “principle of survival of the fittest” to select more suitable trial solutions by dealing with a population of solutions simultaneously. Each solution is represented by a binary, integer or real valued string called a chromosome. By applying three genetic operators: selection, crossover and mutation to the chromosomes, GAs maintain good solutions in the current population of solutions and explore the search space for better solutions. The search process terminates when the stopping criteria are met.

Traditionally, GAs have generally been applied to optimization problems that have one objective. However, most problems in the real world have more than one objective that needs to be satisfied. Therefore, a number of multi-objective genetic algorithms, including the Vector Evaluated Genetic Algorithm by Schaffer (1984), the Weight-Based Genetic Algorithm by Hajela and Lin (1993), the Multi-Objective Genetic Algorithm by Fonseca and Fleming (1993) and the Strength Pareto Evolutionary Algorithm by Zitzler and Thiele (1998) have been developed to solve real world multi-objective problems (Deb, 2002). In this study, a multi-objective genetic algorithm called WSMGA (Water System Multi-objective Genetic Algorithm) has been used to solve both the single-objective and multi-objective problems presented in this paper. WSMGA is based on the state-of-the-art multi-objective generic algorithm NSGA-II (Deb et al., 2002) and is described in more detail in Wu et al. (2010b).

6.2.3 Carbon pricing

Emissions trading is one of the most popular schemes for controlling GHG emissions. In most emissions trading schemes, a cap and trade approach is used. Under a cap and trade approach, emission permits are usually issued by the government. Businesses must have sufficient permits to cover the GHG emissions they produce each year. These permits can be sold or purchased in the marketplace (Prime Ministerial Task Group on Emissions Trading, 2007). Ideally, the carbon price is based on the social cost of carbon, which normally refers to the cost to mitigate climate change (reduce GHG emissions) or the marginal social damage from a tonne of emitted carbon (Guo et al., 2006). However, the actual carbon price is often determined by the market (Prime Ministerial Task Group on Emissions Trading, 2007). The average world market price of a tonne of GHGs in the form of CO₂-e in 2005-06 was around \$US20 - \$US25 (Mitchell et al., 2007). In order to achieve long-term abatement, the carbon price is expected to rise over time (Prime Ministerial Task Group on Emissions Trading, 2007). In the literature, there are many

estimates of possible future carbon prices based on different scenarios. The Australian Bureau of Agricultural and Resource Economics (ABARE) estimates carbon prices to range from \$A28 to \$A46 per tonne of CO₂-e for an international market and from \$A15 to \$A31 per tonne of CO₂-e for an Australian abatement market in 2030 (Prime Ministerial Task Group on Emissions Trading, 2007). However, the actual social cost of carbon could be higher. Sterner and Persson (2007) suggest that a marginal social cost of carbon could reach over \$US400 per tonne of C (carbon) by 2050, which is equivalent to about \$US110 or \$A120 per tonne of CO₂-e. As a result, four carbon prices ranging from \$A10 to \$A120 per tonne of CO₂-e (\$A10, \$A30, \$A60 and \$A120) have been used in this paper. It should be noted that actual market carbon prices will vary with time. However, the constant carbon prices adopted in this paper are sufficient to illustrate the impact different carbon prices are likely to have on the tradeoffs between cost and GHG emissions, as they cover the likely range of expected values.

In order to focus on the comparison of the single- and multi-objective approaches for the WDS optimization problem proposed in this study and simplify the optimization framework, only the indirect GHG emissions from manufacturing of network components and operation of these systems are incorporated into the optimization process via a price of carbon.

6.2.4 Present value analysis

In economics, time preference is generally accounted for by using present value analysis (PVA) (Tietenberg, 1997). In practice, a discount rate equal to the cost of capital (around 6 to 8%) is usually used. However, in the planning of social projects, such as WDSs, PVA with a discount rate that represents the social cost is required to translate the costs from far in the future to the present, enabling effects occurring at different times to be compared. The selection of appropriate discount rates for projects with long term social and/or environmental impacts, which will potentially be spread out over hundreds of years, remains a controversial issue. For traditional project

planning, in which only economic costs are considered, the controversy mainly lies in selecting the correct discount rate. However, for a multi-objective design, such as the situation described in this paper, the controversy is twofold. The first issue is selecting the correct discount rate and the second issue is whether or not the discount rate used for one design objective, such as economic costs, should also be used for the other design objective, such as GHG emissions.

In terms of the first issue, constant discount rates ranging from 2% to 10% are generally used by government agencies and organizations (Rambaud and Torrecillas, 2005). Many water utilities adopt a rate close to the cost of capital (around 6% to 8%). Therefore, a discount rate of 8% has been selected in relation to system economic or monetary cost for illustration purposes in this paper. In terms of the second issue, some researchers suggest that the same discount rate should be used for carbon as for money (van Kooten et al., 1997). However, others such as Fearnside (2002) argue that the discount rate used for GHGs should be different from that used for capital. In practice, a zero discount rate is often used for GHGs (Fearnside, 1995). For example, the IPCC has adopted a zero discount rate with a 100-year time horizon for the calculation of GHG emission impacts in its Second Assessment Report (Fearnside, 2002). Based on the IPCC recommendation, a zero discount rate has been assumed for calculating GHG emission costs in this paper. For a detailed treatment of the impact of discount rate on tradeoffs between cost and GHG emissions for WDSs, the reader is referred to Wu et al. (2010).

6.3 Case studies

6.3.1 Case study 1

Case study 1 description

The network configuration for this system is shown in Figure 6.3 and the design conditions are summarized in Table 6.1. The aim of the design is to select the best combination of pump and pipe sizes that minimize both the system cost and GHG emissions of the network. In the optimization process, the following demand loading cases are used to select appropriate networks:

- 1) The system of selected pipe sizes and pump must be able to deliver at least the average flow(s) on the peak day to the tank(s).
- 2) If the network can deliver the average flow on the peak day, an average-day flow based on a 48-hour extended period simulation (EPS) with the diurnal water demand curve shown in Figure 6.2 is used to estimate the average annual energy consumption due to pumping, enabling the average annual operating costs and emissions of the system to be computed. If the network is unable to deliver the average flow on the peak day, it is removed from further consideration.

For both case studies, water needs to be pumped from a reservoir into storage tanks, which are assumed to be 5 m high. During the EPS, the lower and upper tank water trigger levels are assumed to be 2 and 4 meters, respectively.

In this paper, seventeen different pump curves for 10 different fixed speed pumps (some pumps have two curves) and 26 ductile iron cement mortar lined (DICL) pipes of different diameters are considered as options in this case study. The pump curves were selected using Thompson Kelly & Lewis' pump selection program EPSILON (2001). The initial pump station cost is taken as part of the capital cost and the pump cost has been used to compute pump replacement/refurbishment costs. The costs of the pumps and corresponding

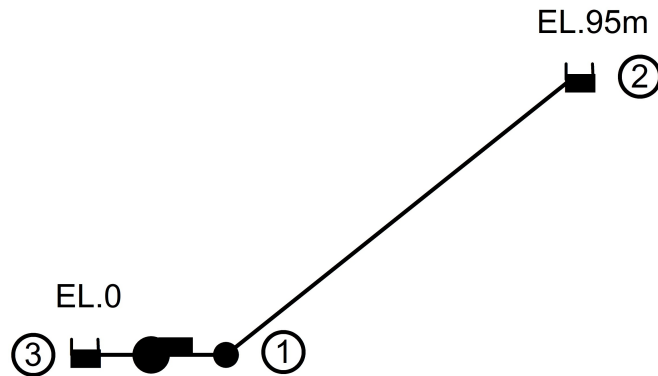


Figure 6.3 Network configuration for case study 1 (tank 2 is the storage tank; the elevation at tank 2 refers to the initial tank water level)

Table 6.1 Design conditions of case study 1

Annual demand (m ³)	Average peak-day flow (L/s)	Pipe length (m)	Design life (years)
2,522,880	120	1,500	100

pump stations have been calculated according to the sizes of the pumps (Wu et al., 2008a). The mass per unit length of the pipes is calculated according to DICL pipe data obtained from Tyco Water. Details of the pumps and pipes are given in Tables 6.2 and 6.3, respectively.

Table 6.2 Pump information [adapted from: Thompson Kelly & Lewis (2001)]

Number	Pump Type	Speed (rpm)	Impeller diameter (mm)	BEP ^a (%)	Q at BEP (L/s)	H at BEP (m)	Rated power (kW)	Station cost ^b (10 ³ \$)	Pump cost (10 ³ \$)
1A	8*17A_ECS-2s	1475	410	83	126	107	159	990	644
1B	8*17A_ECS-2s	1475	432	83	130	120	183	1,086	723
2A	8*17B-3s	1475	393	82	112	118	158	988	643
2B	8*17B-3s	1475	445	84	130	154	233	1,263	875
3A	8*17B_ECS-2s	1475	445	84	130	104	158	985	640
4A	8HN124A	2950	293	79	175	95.9	209	1,181	803
5A	6LG13/A	2900	311	80	109	117	155	975	633
5B	6LG13/A	2900	321	81	113	125	171	1,039	684
6A	430DMH-4s	1480	275	84	157	94.6	173	1,047	690
6B	430DMH-4s	1480	312	85	180	121	251	1,320	926
7A	430DMH-5s	1480	251	84	142	99.2	164	1,011	662
7B	430DMH-5s	1480	312	85	180	151	313	1,502	1,097
8A	430DML-5s	1480	290	82	131	101	159	989	644
8B	430DML-5s	1480	313	82	140	118	197	1,138	767
9A	430DML-6s	1480	272	81	123	107	158	988	643
9B	430DML-6s	1480	313	82	140	142	238	1,277	888
12A	460DKL-4s	1480	295	84	162	90.7	171	1,038	683

^aBEP: Best efficiency point; ^bAll costs in the case studies are in Australian dollars unless noted otherwise.

Table 6.3 Ductile iron cement mortar lined (DICL) pipe information

Number	Diameter (mm)	Unit cost (\$/m)	Unit mass	Number	Diameter	Unit cost (\$/m)	Unit mass
1	100	228	18	14	900	2,012	310
2	150	307	30	15	960	2,040	337
3	225	433	51	16	1,000	2,142	356
4	300	568	74	17	1,050	2,270	379
5	375	813	99	18	1,085	2,360	396
6	450	1,033	126	19	1,220	2,655	461
7	525	1,252	154	20	1,290	2,860	496
8	600	1,415	183	21	1,350	2,996	526
9	675	1,658	213	22	1,500	3,337	603
10	700	1,739	223	23	1,650	3,678	683
11	750	1,900	244	24	1,800	4,020	765
12	800	1,950	266	25	1,950	4,361	849
13	825	1,976	277	26	2,100	4,696	935

Results from case study 1

The search space for this case study has only 442 solutions. Therefore, instead of genetic algorithm optimization, full enumeration and non-dominated sorting of all enumerated solutions have been used to optimize this system. As a result, the optimization results are true Pareto-optimal solutions. A total of eight solutions were found along the Pareto-optimal front for this case study. These solutions are denoted as numbers 1 to 8 in order of increasing initial capital cost of the pipelines. The larger the number is, the larger the capital cost of the pipeline. The network configuration and characteristics of these eight solutions found on the Pareto-optimal fronts are summarized in Table 6.4. The Pareto-optimal fronts and the single-objective optimal solutions obtained for each of the different carbon prices are plotted in Figure 6.4. The numbers next to the solution points in Figure 6.4 are the corresponding design numbers in Table 6.4. The single-objective optimal solutions are represented with an unfilled symbol. For example, in Figure 6.4(a), Design 2 is the second lowest system cost solution found when a carbon price of \$10/tonne of CO₂-e is used in the multi-objective optimization. The diameter of the pipe is 375 mm as shown in Table 6.4. Design 2 is also the lowest total cost solution obtained using the single-objective approach with the same carbon price. The water level fluctuation in the tank and the variation of the flow over the 48-hour EPS period for Designs 1 and 8 are also plotted in Figure 6.4.

In the single-objective optimization, as expected, only the least total cost network is found for each carbon price considered, as shown by the unfilled symbol solutions in Figure 6.4. The single-objective optimal solution is dependent on the carbon price used and higher carbon prices tend to result in solutions with larger pipes, as expected. Figure 6.4 shows that carbon prices of \$10, \$30 and \$60/tonne CO₂-e lead to an optimal design with a pipe diameter of 375 mm [Design 2 in Figures 6.4(a), 6.4(b) and 6.4(c)], while the higher carbon price of \$120 per tonne of CO₂-e results in an optimal solution with a pipe of 450 mm in diameter [Design 3 in Figure 6.4(d)]. This is

Table 6.4 Pareto-optimal solutions found for case study 1 (Cost: $i=8\%$; GHG $i=0\%$)

Design number	Pump number	Pipe diameter (mm)	Pipe cost (M\$)	Pipe GHG (kt)	Average annual energy		Total GHG over 100 years (kt)
					over first 50 years (10^3 kWh)	over second 50 years (10^3 kWh)	
1	1B	300	0.85	1.29	999	1,052	108.2
2	3A	375	1.22	1.73	871	890	93.4
3	3A	450	1.55	2.19	847	854	90.8
4	3A	525	1.88	2.68	838	841	90.2
5	12A	525	1.88	2.68	831	837	89.6
6	6A	525	1.88	2.68	830	835	89.4
7	12A	600	2.12	3.19	825	828	89.3
8	6A	600	2.12	3.19	823	826	89.1

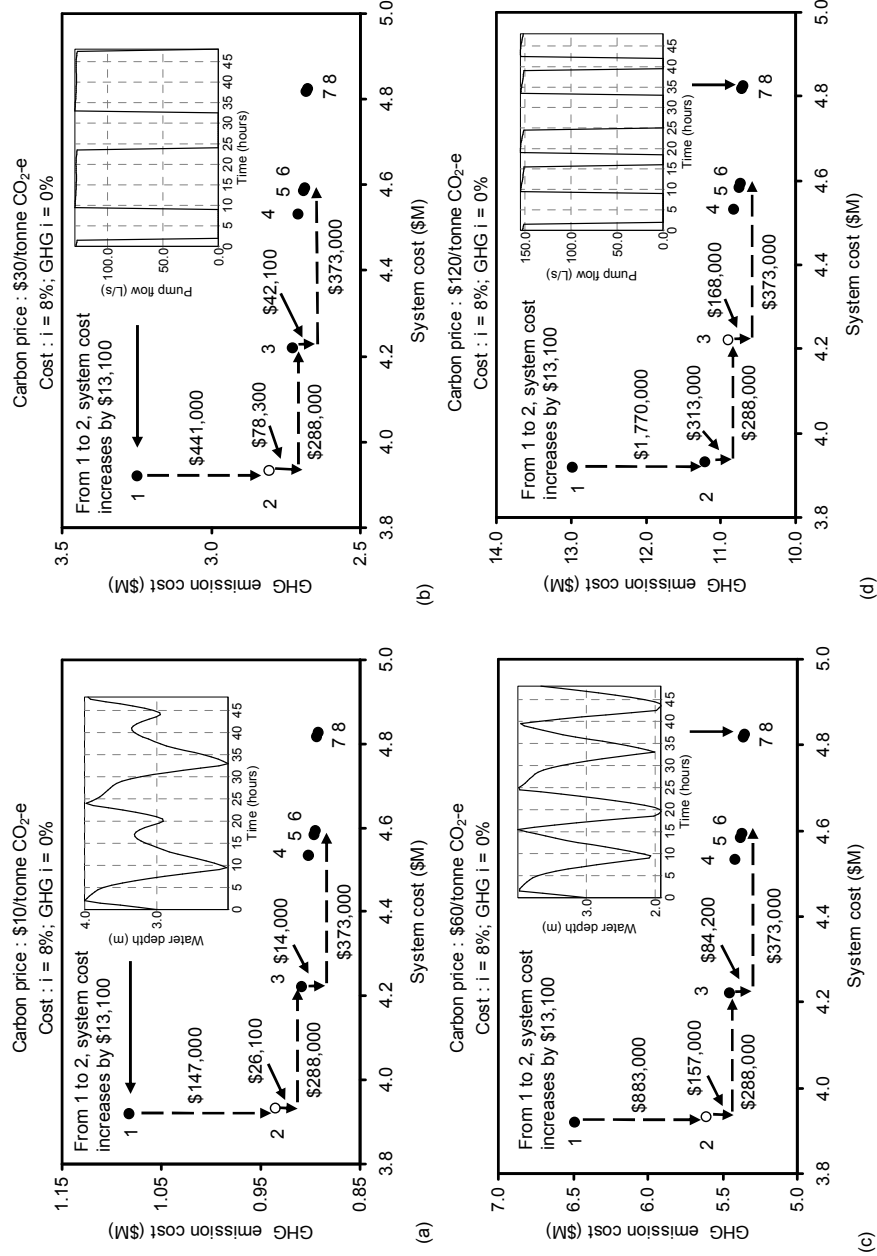


Figure 6.4 Optimization results of case study 1 (the unfilled symbol represents the single-objective optimization solution obtained using the corresponding carbon price; and the network configurations corresponding to the design numbers are shown in Table 6.4)

because the increase in carbon price increases the impact the GHG cost has on the total cost. Consequently, when a higher carbon price is used, a network with larger pipe size, which has less friction loss and generates fewer operating GHG emissions, is more likely to be selected.

Figure 6.4 shows that in the multi-objective optimization, an ordered set of Pareto-optimal solutions is found for each carbon price considered. These Pareto-optimal solutions include the lowest system cost solution, the lowest GHG emission cost solution, and other non-dominated solutions in-between. These Pareto-optimal solutions show significant tradeoffs between the two objectives. When a carbon price of \$10 per tonne of CO₂-e is used [see Figure 6.4(a)], from Design 1 (the lowest system cost solution) to Design 2, a \$13,100 increase in system cost results in a \$147,000 reduction in GHG emission cost. From Design 2 to Design 3, a \$288,000 increase in system cost results in a \$26,100 reduction in GHG cost. From Design 3 to Design 6, a \$373,000 increase in system cost only results in a \$14,000 reduction in GHG cost. These tradeoffs are highly carbon price dependent, as expected. For example, Figure 6.4(d) shows that when the carbon price is increased to \$120/tonne of CO₂-e, from Design 1 to Design 2, a \$13,100 increase in system cost leads to a \$1.77 million decrease in GHG costs, which is more than \$1.6 million higher than the decrease in GHG costs when a carbon price of \$10/tonne of CO₂-e is used. It should be noted here that the optimization results also rely on the discount rate used. However, this is not the focus of this study and as mentioned previously, details of the impact of different discount rates on the tradeoffs between costs and GHG emissions are given in Wu et al. (2010).

In addition, in the multi-objective optimization, it has been found that the carbon price used has no impact on the ordered set of optimal solutions that are spread out along the Pareto front. Figure 6.4 shows that the same ordered set of Pareto-optimal solutions is found no matter which carbon price is used. This is because the carbon price here only changes the scale of the second objective function values; however, it does not have any impact on the relative ranking of the Pareto-optimal solutions found for this case study. Therefore,

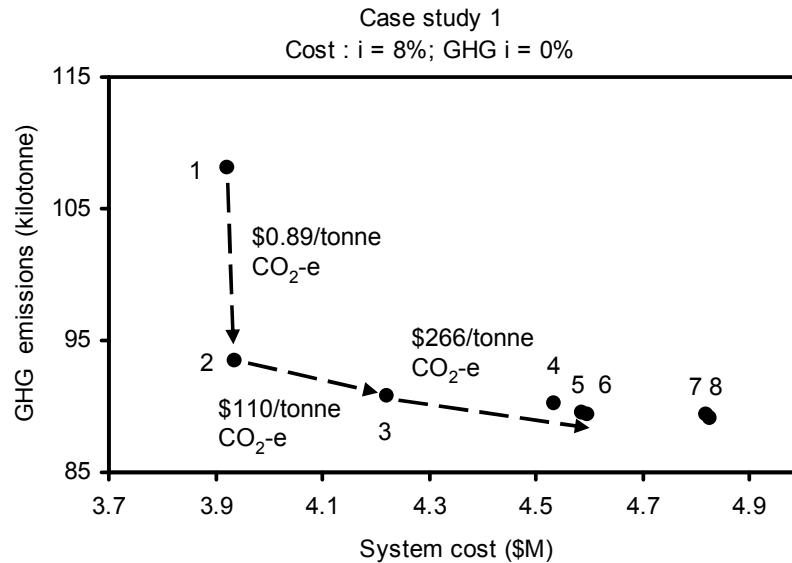


Figure 6.5 Carbon cost mapping of the optimal solution space of case study 1

the tradeoffs between the two objectives can also be represented by the dollar cost to reduce GHG emissions by one tonne, as shown in Figure 6.5. The tradeoffs represented by the dollar cost per tonne of GHGs are independent of the market carbon price used. For example, to move from Design 1 to Design 2, a \$13,100 increase in the system cost results in a 14.8 kilotonnes reduction in GHG emissions over the design life of the system, which can be calculated from the information provided in Table 6.4. Therefore, the cost to reduce one tonne of GHG emissions from Design 1 to Design 2 is equal to \$0.89/tonne $\text{CO}_2\text{-e}$, as shown in Figure 6.5. This cost is increased to \$110/tonne $\text{CO}_2\text{-e}$ from Design 2 to Design 3, and \$266/tonne $\text{CO}_2\text{-e}$ from Design 3 to Design 6. This presentation of the tradeoffs leads to a new way of identifying the single-objective optimal solution by using a carbon cost mapping of the optimal solution space, as shown in Figure 6.5.

In order to obtain this carbon cost mapping, a convex optimal front needs to be defined from within the Pareto-optimal front. A convex optimal front is the set of piece-wise linear lines connecting the non-dominated solution points,

for which the sequence of slopes is non-decreasing. By calculating the dollar cost to reduce one tonne of GHG emissions between two adjacent solutions on the convex optimal front, a carbon cost mapping of the optimal solution space can be obtained. With this carbon cost mapping, the single-objective optimization solution (or the lowest total cost solution) for a given market carbon price can be found easily without the need for any additional optimization runs. For example, for this case study, when the carbon price is between \$0.89 and \$110/tonne CO₂-e (see Figure 6.5), Design 2 with a pipe size of 375 mm is the single-objective optimal solution [see Figures 6.4(a) to 6.4(c)]; and when the carbon price is between \$110 and \$266/tonne CO₂-e (again see Figure 6.5), Design 3 with a pipe size of 450 mm is the single-objective optimal solution [see Figure 6.4(d)].

6.3.2 Case study 2

Case study 2 description

The network configuration of the second case study is shown in Figure 6.6. The network consists of a water source (reservoir 6), a pump, eight pipes and three tanks, each of which has an initial water level of 90 m. The aim of this case study is to minimize both system cost and GHG emissions of the network, while being able to deliver at least the average flow on the peak day to each tank. In the optimization process, the same demand loading cases as those used in the first case study are used to select appropriate networks for this case study. The design conditions are summarized in Table 6.5. The options for the pump are the same as those presented in Table 6.2. The sizes of the pipes can only be selected from the first 16 choices presented in Table 6.3, as the larger pipes were identified as being too big and were therefore not considered in the optimization analysis.

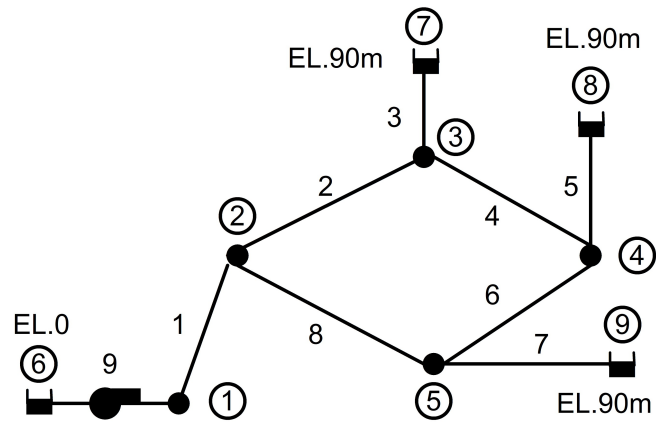


Figure 6.6 Network configuration for case study 2 (tanks 7, 8 and 9 are storage tanks; the elevations at tanks 7, 8 and 9 refer to the initial tank water level)

Table 6.5 Design conditions of case study 2

Total annual demand (m ³)	Ave. peak-day Q for each tank (L/s)	Pipe length (km)							
		1	2	3	4	5	6	7	8
2,522,880	40	1.0	1.2	0.5	1.0	0.5	1.0	0.5	1.5

Results from case study 2

The WSMGA computer optimization program was used to optimize the second network. In the GA optimization process, a population size of 500, 3000 generations, a crossover probability of 0.9 and a mutation probability of 0.1 were used. These GA parameter values were selected using a series of sensitivity tests, in which the combination of the parameter values generated consistent Pareto-optimal fronts within a reasonable execution time. Keedwell and Khu (2006) pointed out that the starting position in the search space is important in order for multi-objective genetic algorithms to find desired solutions. Consequently, one hundred random seeds (i.e. random starting positions) have been used in this study to assess the consistency of the performance of WSMGA.

The Pareto-optimal fronts and the single-objective optimal solutions for the second case study obtained using different carbon prices are plotted in Figure 6.7. The single-objective optimal solutions are again represented with unfilled symbols. The network configurations of six typical convex solutions found in this case study are presented in Table 6.6. The pipeline cost, annual energy consumption and GHG emissions of these solutions are presented in Table 6.7. These solutions are ranked from 1 to 6 according to the initial capital cost of the pipelines. The larger the number is, the larger the initial capital cost of the pipelines. The numbers next to the solution points in Figure 6.7 are the corresponding design numbers in Tables 6.6 and 6.7.

In the single-objective optimization, the carbon price used has a significant impact on the results. As found in the first case study, higher carbon prices tend to result in solutions with larger pipes. For example, Figure 6.7 shows that a carbon price of \$10/tonne CO₂-e results in a single-objective optimal solution with pipe cost of \$3.52 M (Design 2 in Table 6.7); while a carbon price of \$30 or \$60/CO₂-e leads to a solution with pipe cost of \$4.10 M (Design 3 in Table 6.7). When the carbon price is further increased to

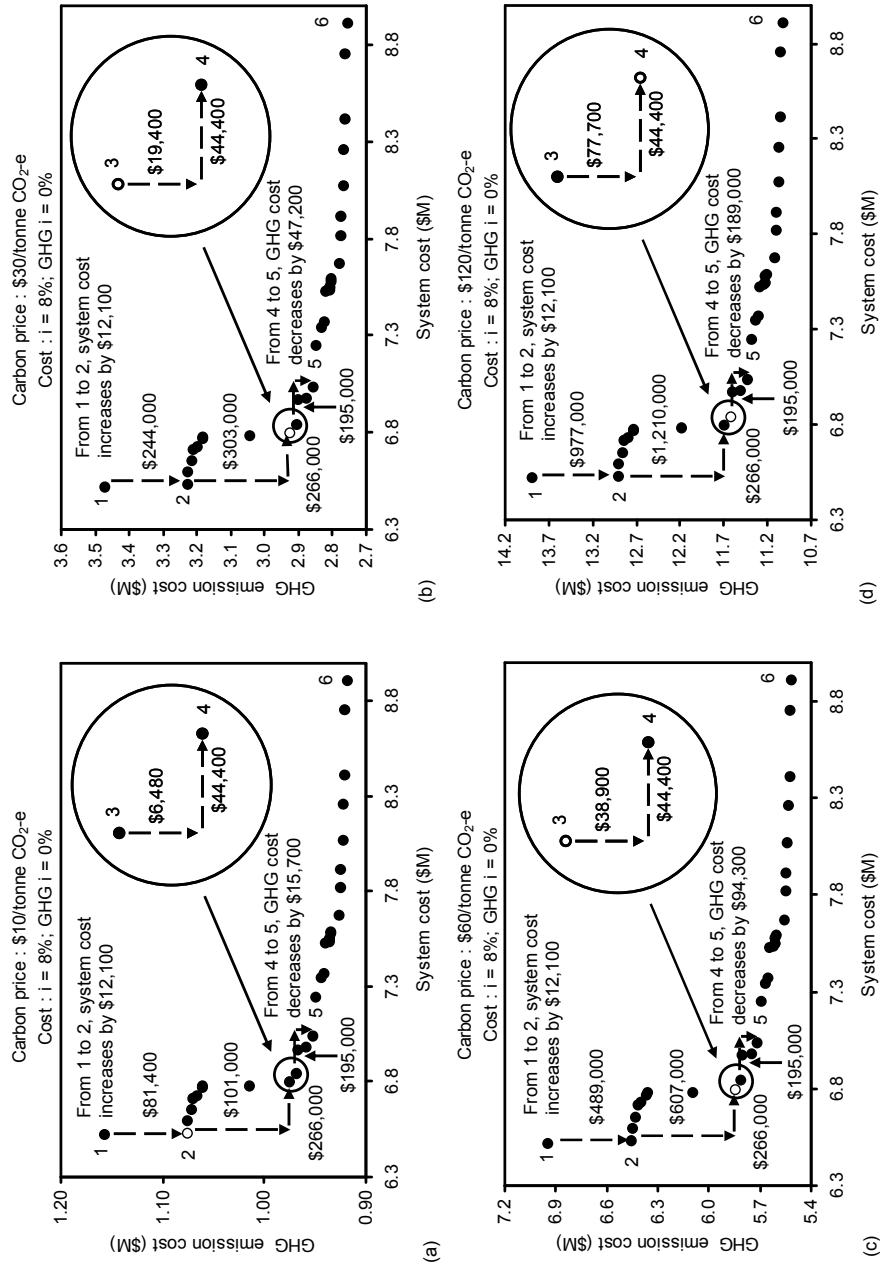


Figure 6.7 Optimization results of case study 2 (the unfilled symbol represents the single-objective optimization solution obtained using the corresponding carbon price; and the network configurations corresponding to the design numbers are shown in Tables 6.6 and 6.7)

Table 6.6 Selected optimal solutions found for case study 2 (Cost: $i=8\%$; GHG $i=0\%$)

Design number	Pump number	Pipe 1 diameter (mm)	Pipe 2 diameter (mm)	Pipe 3 diameter (mm)	Pipe 4 diameter (mm)	Pipe 5 diameter (mm)	Pipe 6 diameter (mm)	Pipe 7 diameter (mm)	Pipe 8 diameter (mm)
1	8B	300	300	225	300	225	100	225	225
2	1B	375	300	225	225	300	100	225	225
3	3A	375	375	225	225	300	150	225	300
4	3A	375	375	225	300	300	100	225	300
5	3A	450	375	225	300	300	100	225	300
6	12A	600	525	375	375	375	100	300	375

Table 6.7 Costs and GHG emissions of selected optimal solutions for case study 2 (Cost: $i=8\%$; GHG $i=0\%$)

Design number	Pipe cost (M\$)	Pipe GHG (kt)	Average annual energy		Total GHG over 100 years (kt)
			over first 50 years (10^3 kWh)	over second 50 years (10^3 kWh)	
1	3.34	4.74	1,023	1,106	115.7
2	3.52	4.9	968	1,002	107.5
3	4.1	5.79	864	895	97.4
4	4.15	5.92	858	886	96.8
5	4.37	6.23	844	864	95.2
6	6.27	8.94	792	799	91.8

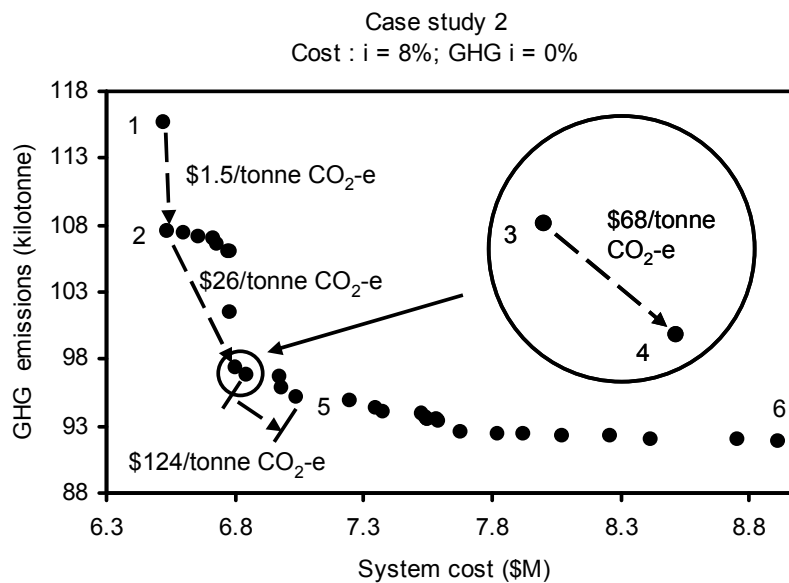


Figure 6.8 Carbon cost mapping of the optimal solution space of case study 2

\$120/tonne $\text{CO}_2\text{-e}$, a network with a pipe cost of \$4.15 M (Design 4 in Table 6.7) is selected.

Similarly to the first case study, an ordered set of optimal solutions is found for each carbon price used in the multi-objective optimization. These optimal solutions also show significant tradeoffs between the two objectives. Figure 6.7(a) shows that when a carbon price of \$10/tonne of $\text{CO}_2\text{-e}$ is used, from Design 1 (the lowest system cost solution) to Design 2 (the second lowest system cost solution), a \$12,100 increase in system cost results in a \$81,400 decrease in GHG emission cost; from Design 2 to Design 3, a \$266,000 increase in system cost results in a \$101,000 reduction in GHG emission cost; and from Design 3 to Design 4, a \$44,400 increase in system cost only leads to \$6,480 decrease in GHG costs. Similar results can also be found between Designs 4 and 5. These tradeoffs are also highly carbon price dependent. Figures 7(b), 7(c) and 7(d) show that when the carbon price increases, the reduction in GHG costs resulting from the same amount of savings in system cost increases accordingly, as would be expected.

As for the first case study, the carbon price used does not have an impact on the relative ranking of the multi-objective optimal solution sets. Therefore, the tradeoffs presented in terms of the dollar costs to reduce one tonne of CO₂-e are again carbon price independent. As shown in Figure 6.8, the cost to reduce one tonne of GHGs is \$1.5/tonne from Design 1 to Design 2, \$26/tonne from Design 2 to Design 3, \$68/tonne from Design 3 to Design 4 and \$124/tonne from Design 4 to Design 5, no matter which carbon price is used. Thus, a carbon cost mapping of the optimal solutions space for this case study is obtained. When the carbon price is between \$1.5 and \$26/tonne CO₂-e (see Figure 6.8), Design 2 is the single-objective optimal solution [see Figure 6.7(a)]; when the carbon price is increased to \$30 and \$60/tonne CO₂-e, which is between \$26 and \$68/tonne CO₂-e, Design 3 is the single-objective optimal solution [see Figures 7(b) and 7(c)]; and when the carbon price is between \$68 and \$124/tonne CO₂-e (again see Figure 6.8), Design 4 is the single-objective optimal solution [see Figure 6.7(d)]. It should be noted here that the solutions between Designs 2 and 3 (see Figure 6.8) are not selected. This is because these solutions are not on the convex optimal front. For the same reason, the solutions between Designs 4 and 5 are not selected.

6.3.3 Discussion

The results from both case studies show that both single-objective and multi-objective approaches have advantages and disadvantages. The single-objective approach is easier to implement and results in a simpler decision making process. In contrast, the multi-objective approach requires more computational effort, as well as domain knowledge and judgment, in order to make a decision. However, the single-objective approach also has significant drawbacks compared to the multi-objective approach.

First of all, in the single-objective approach an implicit weighting is introduced into the objective function evaluation process when the two objectives are converted into one combined objective. Thus, this approach

results in a loss of information between the two conflicting objectives (i.e. information about the relative tradeoffs between objectives at various carbon prices is lost). Secondly, even though the tradeoffs between the two objectives do not necessarily need to be considered at the decision making stage when the single-objective approach is used, these tradeoffs still need to be dealt with at some stage, in this case, the carbon pricing stage. However, at the carbon pricing stage, consideration of the tradeoffs between the two objectives is implicit. Therefore, as mentioned above, information about the actual tradeoffs between the two objectives is lost. Thirdly, whether or not the carbon price (either determined by evaluation methods or by the carbon market) can present a fair resolution among all stakeholders is uncertain. Also, it is uncertain how accurately the carbon price can reflect the actual cost of carbon, especially if the carbon price is determined by the market only. These uncertainties can be passed to the WDS design process by using a single-objective approach. Fourthly, the single-objective approach is based on the assumption of perfect substitutability, in which one dollar worth of damage caused by GHG emissions can be compensated by a dollar worth of economic growth (Stern and Persson, 2007). However, perfect substitutability in mitigating global warming is not widely accepted. Many proponents of sustainability believe that the damage to future global environmental systems due to global warming cannot be compensated by higher material richness of future generations (Neumayer, 1999). Based on this belief, the environmental objective of minimizing GHG emissions should be optimized independently from system costs by employing a multi-objective optimization approach.

Finally, the single-objective approach of incorporating GHG emission minimization into the optimization of WDSs corresponds to the weighted sum method of solving multi-objective optimization problems (Deb, 2002). Therefore, by repeating the single-objective optimization with different carbon prices, various multi-objective optimal solutions can be identified. However, it is often difficult to determine the appropriate weights for multi-objective function values in the weighted sum method, which is equivalent to the carbon prices in the single-objective approach in this study, so that a satisfactory spread of multi-objective optimal solutions along the Pareto-

optimal front is obtained (Das and Dennis, 1997; Deb, 2002). It has also been proven that not all multi-objective optimal solutions can be found by using the weighted sum method (Miettinen, 1999).

Since the carbon price has no impact on the relative ranking of the multi-objective optimal solutions, the multi-objective optimization formulation presented in this paper can be easily converted into a multi-objective optimization problem in which the system cost in dollars and GHG emissions in tonnes of CO₂-e are minimized. The single-objective approach proposed in this paper is closely related to this multi-objective approach by using a carbon cost mapping of the optimal solution space, as shown in Figures 6.5 and 6.8. This carbon cost mapping of the optimal solution space obtained by using the multi-objective approach provides decision makers with a clear indication of the relative effectiveness of their selected carbon price in reducing GHG emissions relative to other carbon prices.

6.4 Summary and conclusions

In this paper, the issue of how to optimize water distribution systems (WDSs) under an emissions trading scheme with a cap and trade approach is investigated by considering carbon pricing. There exist two ways to incorporate the minimization of GHG emissions into the optimization of WDSs based on a price of carbon: either a single-objective approach or a multi-objective approach. In the single-objective approach, the total cost, which is the sum of the system cost and the costs from GHG emissions based on a price of carbon, is optimized as the sole objective. In the multi-objective approach, the conventional objective of minimizing system cost and the second objective of minimizing GHG emissions via a price of carbon are optimized independently. Two case studies have been used to investigate the relationship between the two approaches. For each case study, two demand loading cases based on the peak day and average day with a 48-hour extended period simulation, and two different pipe roughness values over time were

used to estimate the average energy consumption of the system due to pumping. In addition, four future possible carbon prices ranging from \$10 to \$120 per tonne of CO₂-e have been used to investigate the impact of market carbon prices on the optimization results.

The optimization results show that the single-objective approach is easier to implement; however, it results in a loss of tradeoff information between the two conflicting objectives. In addition, the assumption of perfect substitutability, which is used to compute the one combined objective, is not widely accepted. In contrast, the multi-objective approach requires more computational effort and domain knowledge; however, it provides decision makers with more detailed information by showing the tradeoffs between the conflicting objectives considered explicitly. In addition, as the carbon price used has no impact on the tradeoffs between non-dominated solutions, the carbon pricing process can be removed from the objective function evaluation process when a multi-objective approach is used. Thus, the resulting multi-objective solutions express the tradeoffs between system cost in dollars and GHG emissions in tonnes. Based on these tradeoffs, a carbon cost mapping (the dollar cost of reducing one tonne of GHGs between two solutions) of the optimal solution space can be obtained. Based on this carbon cost mapping, the single-objective optimal solution for a given market carbon price can be determined within the set of Pareto-optimal solutions without the need for additional optimization. In this way, the multi-objective approach provides decision makers with a clear indication of the relative effectiveness of their selected carbon price in reducing GHG emissions relative to other carbon prices.

In conclusion, considering the comparison of the single-objective and multi-objective approaches, a multi-objective approach considering system cost in dollars and GHG emissions in tonnes is recommended for the optimization of WDSs accounting for GHG emissions, even under an emissions trading scheme with a cap and trade approach where the GHG emissions can be traded based on a carbon price.

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Chapter 7

Incorporation of variable-speed pumping in multiobjective genetic algorithm optimization of the design of water transmission systems

Publication 3

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Although the manuscript has been reformatted in accordance University guidelines, and sections have been renumbered for inclusion within this thesis, the paper is otherwise presented herein as accepted.

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Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.

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Abstract

Global warming caused by human activities presents serious global risks. Individuals, governments and industries need to be more energy efficient and contribute to the mitigation of global warming by reducing their greenhouse gas (GHG) emissions. In previous research, GHG emission reduction has been identified as one important criterion in improving the sustainability of urban infrastructure and urban water systems. Within the water industry, opportunities exist for reducing GHG emissions by improving pumping efficiency via the use of variable-speed pumps (VSPs). Previously, VSPs have been used in the optimization of the operation of existing water distribution systems (WDSs). However, in WDS design optimization problems, fixed-speed pumps (FSPs) are commonly used. In this study, a pump power estimation method, developed using a false position method based optimization approach, is proposed to incorporate VSPs in the conceptual design or planning of water transmission systems (WTSs), using optimization. This pump power estimation method is implemented within the solution evaluation process via a multiobjective genetic algorithm approach. A case study is used to demonstrate the application of the pump power estimation method in estimating pump power and associated energy consumption of VSPs and FSPs in WTS optimization. In addition, comparisons are made between variable-speed pumping and fixed-speed pumping in multiobjective WTS optimization accounting for total cost and GHG emissions. The results show that the use of variable-speed pumping leads to significant savings in both total cost and GHG emissions from WTSs for the case study considered.

7.1 Introduction

Global warming caused by increased concentration of greenhouse gases (GHGs) in the atmosphere is a significant threat facing our generation. Extreme weather conditions, such as severe droughts, floods and hurricanes, which are exacerbated by global warming, are already affecting a large number of people around the world. However, more GHGs are still being added into the atmosphere by human activities, such as burning fossil fuel for energy. Consequently, individuals, governments and industries need to be more energy efficient and contribute to the mitigation of global warming by reducing their GHG emissions.

In a number of studies, the minimization of GHG emissions has been identified as one important criterion for improving the sustainability of urban infrastructure and urban water systems (Sahely et al., 2005; Fillion, 2008). Within the water industry, GHG emissions are mainly generated from system operation related to pumping. In a study by Tarantini and Ferri (2001), the authors found that pumping had the highest environmental impact on the water and wastewater system of Bologna in Italy. In a similar finding, a survey conducted by the South Australian Water Corporation showed that major pumping accounts for 46% of GHG emissions from their activities across South Australia (Kelly, 2007). Consequently, opportunities exist within the water industry for GHG emission reduction by improving pumping efficiency.

In order to reduce GHG emissions in the water industry, tradeoffs between GHG emission minimization and the traditional objective of economic cost minimization have been investigated via a multiobjective approach in previous studies (Wu et al., 2008a; Wu et al., 2010a; Wu et al., 2010b). The authors found that a moderate increase in capital investment can result in substantial reductions in GHG emissions from water distribution systems (WDSs). In these studies, a number of commercially available fixed-speed pumps (FSPs) were used as decision variables. FSPs have smaller capital

costs compared with variable-speed pumps (VSPs). However, VSPs have many advantages over FSPs in terms of performance. As Wood and Reddy (1995) pointed out, VSPs provide easier control over the system, which enables a better response to abnormal situations, such as fire and breakage. More importantly, pressures or flowrates can be maintained very close to minimum allowable levels by using VSPs, thus, there is great potential for saving energy and hence for reducing GHG emissions in new pumping systems (Lingireddy and Wood, 1998). Therefore, it is important to consider the incorporation of VSPs in WDS optimization when investigating total cost and GHG emissions from WDSs.

VSPs have been incorporated in the optimization of the *operation* of existing WDSs in previous studies (Wegley et al., 2000; Rao and Salomons, 2007; da Costa Bortoni et al., 2008; Wu et al., 2009). However, for the optimal design of WDSs involving pumping, FSPs have often been used, despite the advantages of VSPs discussed above. One reason for this is that FSPs are commonly used in existing WDSs. In addition, FSPs can be easily simulated in an optimization process by using a fixed pumping head or a pump curve (Duan et al., 1990; Wu et al., 2010a; Wu et al., 2010b), whereas the dynamic features of VSPs make their simulation within optimization iterations a more difficult task.

In previous studies, commercially available FSPs have been used as decision variables in WDS optimization (Wu et al., 2010a; Wu et al., 2010b). However, there is a significant drawback to this approach. This is because it is not practical to include all available pumps as decision variable options in the optimization process due to limited availability of pump information and the high computational effort required to include a large number of pump options in a multiobjective optimization process. When limited numbers of real pumps are used in the WDS optimization process, the optimization may favor network configurations that match the characteristics of the selected pumps. Therefore, a generic approach to pump sizing and pump power estimation, which allows easy adjustment of pump power based on specific network configurations, is more appropriate for WDS optimization (Hodgson and

Walters, 2002). This allows different network configurations generated as part of the WDS optimization process to be compared fairly without introducing distortions resulting from use of a specific pump.

In order to be able to incorporate VSPs into the conceptual design or planning of WDSs using optimization and ensure different network configurations generated during the optimization process are compared fairly, a generic pump power estimation method is required. In this paper, such an approach is proposed for water transmission systems (WTSs), which are the portion of a WDS that delivers water from water sources into storage facilities, such as reservoirs and/or tanks. The proposed method does not directly deal with the simulation of a particular VSP or an existing WTS with VSPs. Instead, it automatically calculates the pump power, and thus the pump energy, required for a particular network configuration, subject to multiple flow constraints. This method is suited to fast and repeated estimation of operating energy consumption of a large number of network configurations, rather than to modeling of the full range of behavior of a particular VSP within an existing WTS. The method can also be used to incorporate FSPs into the conceptual design or planning of WTSs using optimization with appropriate assumptions, provided FSPs are treated as a special case of VSPs.

7.2 Methodology for incorporating VSPs in conceptual design or planning of WTSs

7.2.1 Problem formulation

The WTS optimization problem considered in this study is illustrated in Figure 7.1. The two objectives considered include: 1) the minimization of the total economic cost of the system; and 2) the minimization of the total GHG emissions of the system. In order to calculate the total economic cost and total

GHG emissions of a WTS, a life cycle analysis and the proposed pump power estimation method are required.

The constraints include equality constraints and inequality constraints, as shown in Figure 7.1. Equality constraints often refer to the physical laws (e.g. the continuity of flow and the conservation of energy) that apply to the network. In practice, these constraints do not need to be considered explicitly in an optimization process, as they are often satisfied automatically by using a hydraulic solver, such as EPANET (Rossman, 2000). The inequality constraints are often design constraints that a WTS needs to satisfy, for example, the minimum flowrates within the system. Some of the inequality constraints can be handled by using the proposed pump power estimation method, which is introduced later in this section.

Estimation of total economic cost

The total economic cost (TEC) of a particular network is defined as

$$TEC = CC(\bar{x}) + OC(\bar{x}, OR) + MC(\bar{x}, MS) + EC(\bar{x}, DM) \quad (7.1)$$

where, CC , OC , MC , and EC are capital cost, operating cost, maintenance cost and end-of-life cost, respectively; \bar{x} represents the decision variables (e.g. pipe sizes, pipe material, etc.); OR and MS are the operational rules and maintenance strategies that will be used; DM represents the disposal/recycling methods used at the end of the service life of the system. The capital cost results from the purchase and installation of network components (e.g. pipes, pumps, valves, tanks etc.), and construction of pump stations, storage facilities, etc. The maintenance and end-of-life costs are functions of the decision variables. Pumps also contribute to these two costs. In addition, the maintenance strategy selected and disposal/recycling methods used at the end of the service life of the system have a significant impact on the values of the maintenance and end-of-life costs. In this study, the pump refurbishment costs are not considered, as they contribute only a relatively

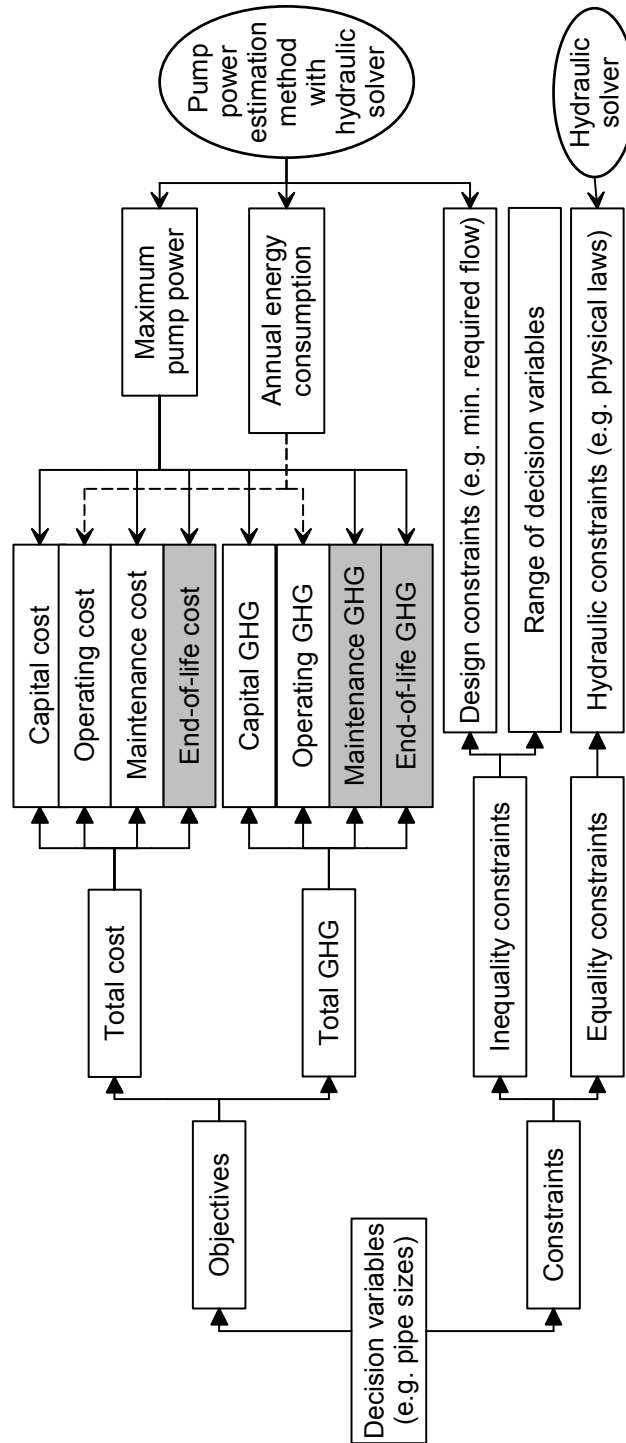


Figure 7.1 Proposed multiobjective WTS design problem

small amount to the total cost once they are converted into their present values (Wu et al., 2010b). It should also be noted that the end-of-life costs of WTSs are often not considered. This is mainly because these costs occur at the very end of the design period of the system, which is often 50 to 100 years for a WTS. Once the end-of-life costs are converted into their present values as part of present value analysis (PVA), the impact of these values on the total cost is usually negligible. In addition, the uncertainty associated with end-of-life costs is often the reason why they are omitted from the analysis.

The operating cost is mainly due to the electricity consumption of system operation related to pumping, which can be calculated based on the annual energy consumption (AEC) as defined below:

$$AEC = \sum_{t=1}^T \frac{P(t)}{\eta(t)_{motor}} \times \Delta t = \sum_{t=1}^T \frac{1}{1000} \frac{\gamma \times Q(t) \times H(t)}{\eta(t)_{pump} \times \eta(t)_{motor}} \times \Delta t \quad (7.2)$$

where, t is the time step [e.g. the time step in an extended period simulation (EPS)]; $P(t)$ is the pump power (kW); γ is the specific weight of water (N/m^3); $Q(t)$ is the pump flow (m^3/s); $H(t)$ is the pump head (m); $\eta(t)_{pump}$ and $\eta(t)_{motor}$ are the pump efficiency and motor efficiency, respectively; T is the number of time steps; and Δt is the duration of each time step (hours). The annual operating cost can be taken as the AEC (kWh) multiplied by the projected average electricity tariff (ET) of the corresponding year (based on an electricity tariff forecasting model). As operating costs occur progressively during the whole design period, PVA needs to be used to convert the operating costs in each year to their present values, in order to allow costs occurring at different times to be compared.

As part of the conceptual design or planning of WTSs, the simplest way to estimate the AEC for each potential solution network in the optimization process is to use the average flowrate during a year. However, the estimation of energy consumption can be improved by using a seasonal EPS, which takes into account the seasonal variation of demand. In both cases, an estimate of

pump power $P(t)$ is required and can be obtained using the proposed pump power estimation method. In addition, in order to account for changes in pipe roughness over the design period, a pipe aging model can be used. Ideally, such a model should take into account any maintenance strategies.

Estimation of total GHG emissions

The total GHG emissions (TGHG) of a particular network are defined as

$$TGHG = CGHG(\bar{x}) + OGHG(\bar{x}, OR) + MGHG(\bar{x}, MS) + EGHG(\bar{x}, DM) \quad (7.3)$$

where $CGHG$, $OGHG$, $MGHG$, and $EGHG$ are capital emissions, operating emissions, maintenance emissions and end-of-life emissions, respectively. These emissions are also functions of decision variables \bar{x} (e.g. pipe size, pipe material, etc.). The capital emissions are mainly due to energy consumption that occurred during the fabrication stage (including material extraction, material production, product manufacturing, and product transportation and installation) of network components during the life cycle of the system (Filion et al., 2004), which can be estimated using embodied energy analysis (EEA) (Treloar, 1994). Emission factor analysis (EFA) can then be used to estimate the capital GHG emissions in the form of CO₂-e (carbon dioxide equivalent) in kilograms (kg) based on the embodied energy values (The Department of Climate Change, 2008). In practice, embodied energy values and emission factors are likely to vary across regions and with time, depending on the material excavation and extraction methods used and the way electricity is generated (e.g. thermal, nuclear, wind, hydroelectricity, etc.). Ideally, a preliminary study should be carried out to determine the embodied energy of the specific types of network components considered and the emission factor values for the study region.

Similar to the operating cost, operating emissions are predominantly caused by system operation related to pumping and therefore, can be calculated using AEC. Once the AEC for a particular future year is estimated using Eq. (7.2), the operating emissions of the year are obtained by multiplying the AEC and

the projected average emission factor of the corresponding year, which can be obtained by using an emission factor forecast model for the study region. The operating emissions due to pumping also occur progressively over the design period; therefore, PVA may be required to convert the operating emissions in each year to their present values.

GHG emissions will also be generated during system maintenance and at the end of system service life, when network components are disposed of or recycled. These emissions are a function of the network components selected at the beginning of the project (that depends on the value of decision variables), the maintenance strategies adopted throughout the life of the project and the disposal methods and recycling options selected at the end-of-life, but are often not considered.

Impact of use of FSPs or VSPs on objective evaluation

Whether FSPs or VSPs are used has an impact on the evaluation of the two objectives. Firstly, VSPs are generally more expensive than FSPs. However, the capital cost of VSPs can be offset by eliminating some network components, such as control valves, bypass lines and conventional starters, which are required by FSPs (Europump and Hydraulic Institute, 2004). Similarly to pipes, the capital emissions of pumps mainly depend on the material of the pump and where it is manufactured (Filion et al., 2004), which have a significant impact on the embodied energy of pumps, rather than whether FSPs or VSPs are used. Therefore, any differences between the capital GHG emissions of FSPs and VSPs are usually small.

As VSPs have a variable frequency drive (VFD), which FSPs do not have, they can incur additional maintenance costs. However, these costs can generally be offset by the maintenance costs for the additional components required by FSPs, as mentioned previously. In addition, VSPs generally operate at lower speeds and have lower loads on the shaft, bearings and gaskets compared to FSPs, which result in lower failure frequency and can reduce maintenance costs significantly (Hovstadius, 2001). In addition, Wu et al. (2010b) showed that the lifecycle maintenance costs for FSPs are a small

percentage of the total cost. Therefore, the difference between the lifecycle maintenance costs of FSPs and VSPs is negligible in the evaluation of the total cost.

The most significant impact of the selection of either FSPs or VSPs is on operating cost and emission estimation. As the speeds of VSPs can be adjusted to maintain flowrates at their minimum allowable levels, the average pump flowrates for VSPs are generally lower (Hovstadius, 2001). As a result, in order to deliver the required demand, VSPs are likely to operate for most of the time during a day. In contrast, FSPs can only operate at a single speed and their average pump flowrates are generally higher than those for VSPs. However, the time during which FSPs are operating is less than that of VSPs, provided they deliver the same quantity of water. The difference between the pump flowrates of FSPs and VSPs has a significant impact on their respective energy consumption (The U.S. Department of Energy's Industrial Technologies Program and Hydraulic Institute, 2006). At higher pump flows, FSPs need to overcome higher friction losses, which are sometimes significant, especially for systems with small pipes. In addition, newer VSPs can also operate at high efficiency (Burt et al., 2006). As a result, the AEC and associated operating costs and GHG emissions of FSPs can be higher compared to those of VSPs. It should be noted that in regions where electricity tariffs are lower during off-peak periods, the operating cost of FSPs can be reduced by scheduling most of the pumping to occur during these periods; however, the GHG emissions associated with pumping cannot be reduced.

7.2.2 Proposed pump power estimation method

FCV based pump power estimation method

For the purpose of calculating the required pumping power for the estimation of maximum pump capacity and AEC, a pump (either VSP or FSP) can be artificially represented by a control valve combined with an upstream reservoir with a high head within a hydraulic solver, as shown in Figure 7.2.

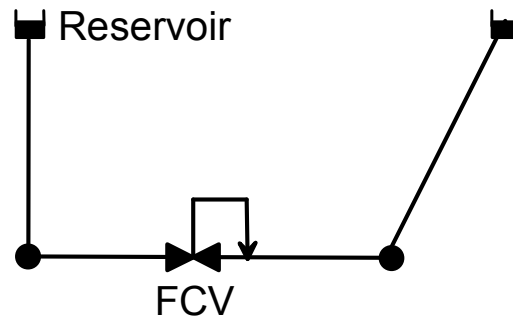


Figure 7.2 Proposed pump power estimation method within a hydraulic solver

For WTSs, where system flow is of primary concern, it is proposed that a flow control valve (FCV) be used as the control valve, as this provides a simple control of system flow.

When estimating pump power for a WTS, an appropriate setting of the FCV needs to be determined, such that the flows into the downstream storage tanks are maintained as close to the required flows as possible. Thus, the task of determining the most appropriate FCV setting for calculating pump power for a WTS is a constrained single-objective minimization problem, which is defined as:

$$\text{minimize} \quad g(y) = \min \{ \mathbf{Q}_a - \mathbf{Q}_r \} \quad (7.4)$$

subject to

$$y \in [Q_L, Q_U] \quad (7.5)$$

$$\mathbf{Q}_a = \{ q_j \} \quad \forall j = 1, 2, \dots, nt \quad (7.6)$$

$$\mathbf{Q}_r = \{ q_j^r \} \quad \forall j = 1, 2, \dots, nt \quad (7.7)$$

$$\mathbf{Q}_a - \mathbf{Q}_r \geq 0 \quad (7.8)$$

where, g is the objective function of the single-objective minimization problem; y is the desired optimum FCV setting; \mathbf{Q}_a and \mathbf{Q}_r are the vectors of actual and required flows into the storage tanks, respectively; Q_L is the lower bound of y , which is often taken as the minimum required flowrate of the system; Q_U is the upper bound of y , which is defined by the user; q_j and q_j^r are the actual and required flows into the storage tank j , respectively; and nt is the number of storage tanks.

By searching for a suitable FCV setting y between Q_L and Q_U , the differences between the actual flows the system delivers into the storage tanks and the corresponding required flows are minimized. The pump head associated with a particular flow distribution can then be obtained from the head of the downstream node of the FCV within a hydraulic solver. Thus, the pump power for the WTS can be calculated.

Pumping energy estimation using the proposed pump power estimation method

The process for estimating pumping energy using the false position method based pump power estimation method for a WTS is illustrated in Figure 7.3. First, the upper and lower bounds of the valve setting need to be defined (Step 1). Then, the false position method, combined with a hydraulic solver, is used to find the FCV setting y such that the objective defined in Eq. (7.4) is minimized and the design constraints are satisfied during time t (Step 2). The pump head can be obtained as the head of the downstream node of the FCV within the hydraulic solver (Step 3). The actual pumping time can be calculated based on the demand during time t (Step 4). Thus, the pumping energy consumption during time t can be computed (Step 5).

Both VSPs and FSPs are sized to meet the same design criteria of the system. As the speed of a VSP can be adjusted to match the required flowrates for a WTS, it is assumed that the valve setting is determined in a way that maintains the flows at just above their minimum allowable levels. However,

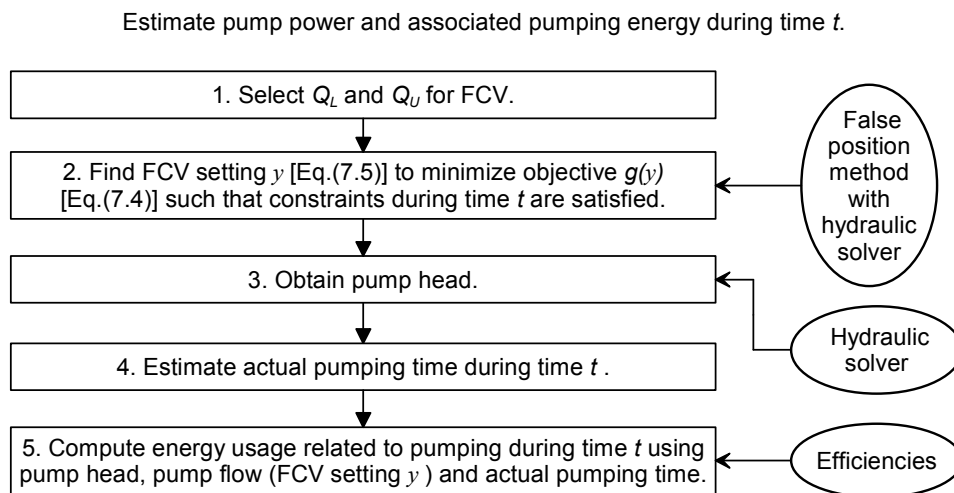


Figure 7.3 Pump power and associated pumping energy estimation processes

when FSPs are used, flowrates will exceed their minimum requirements. As a result, FSPs will operate for fewer hours compared to VSPs when the same volume of water is delivered in a WTS.

The false position method (Burden and Faires, 2005) has been selected for the purpose of solving the constrained single-objective valve setting search problem because it is a bracketing method, which is guaranteed to converge. This is essential in an optimization process, as an estimate of pump power has to be made for each potential network solution at each iteration to ensure a fair comparison between different networks is made.

7.2.3 Solution evaluation process within a genetic algorithm framework

The proposed solution evaluation process, incorporating the pump power estimation method for WTSs, within a genetic algorithm framework is illustrated in Figure 7.4.

There are five steps in evaluating a network solution, which are marked from 1 to 5 in the figure. The proposed pump power estimation method is employed in Steps 2 and 4 for estimating the maximum required pump capacity and annual energy consumption, respectively. In the first step, a threshold test is performed to determine whether or not the current solution network needs to be evaluated. A threshold value for the valve setting is first defined, often as the upper bound of the valve setting for estimating the maximum capacity of the pump. If the current solution can satisfy the design requirements when the valve setting is set at the threshold value, the solution is evaluated. Otherwise, the network is considered to be infeasible and removed from further consideration in order to reduce the size of the search space during the optimization process, thereby increasing computational efficiency and the chances of finding a globally optimal solution.

Once a solution has passed the threshold test, the maximum pump power required is calculated based on the design criteria defined for the case study under consideration using the proposed pump power estimation method (Step 2). For example, a WTS is often designed to meet the average flow on a peak-day (referred to as peak-day flow in this paper) during the highest demand year of the design period. The pump related costs and emissions can be estimated based on the maximum pump power of the pump. Thus, the capital cost and emissions of the solution network can be calculated (Step 3).

The fourth step is to calculate the annual energy consumption (AEC) and associated operating cost and emissions, and in turn, the total operating cost and operating GHG emissions of the system during its design life. In this step, the proposed pump power estimation method is used to estimate the pump power and pumping energy for each time step t . The AEC can be calculated by summing the actual pumping energy of each time step t . Once the AEC has been obtained, the operating cost and GHG emissions of the corresponding year can be calculated based on the electricity tariff and emission factor of that year and thus, the total cost and GHG emissions can be calculated (Step 5).

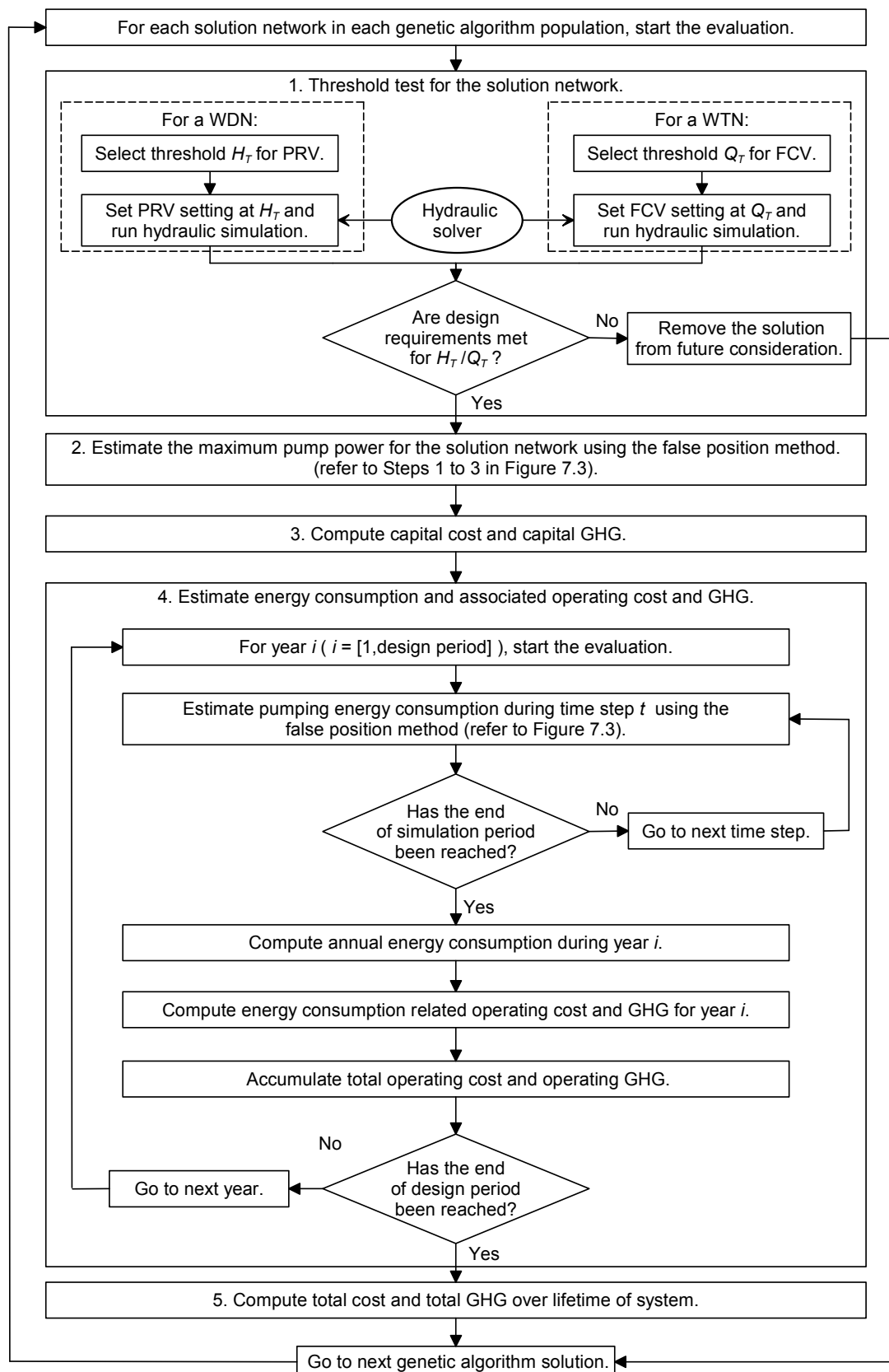


Figure 7.4 Proposed solution evaluation process within a genetic algorithm

7.3 Case study

In this paper, a case study is used to demonstrate the application of the proposed pump power estimation method in multiobjective WTS optimization accounting for total economic cost and GHG emissions and investigate the impact of variable-speed pumping on the optimization results. The case study network and assumptions made in the objective and solution evaluation processes are presented in this section.

7.3.1 Example network

The network configuration of the case study used to illustrate the approach introduced in this paper is shown in Figure 7.5. For this case study, water needs to be delivered from a water source (reservoir 6) to three storage reservoirs (reservoirs 7, 8 and 9). The demands of the three storage reservoirs are assumed to be the same (i.e. one third of the total annual demand). This case study is a network conceptual design problem, in which pipe diameters are decision variables, and pumps are sized and pump power is calculated using the proposed pump power estimation method for each network configuration determined by the pipes. Sixteen ductile iron cement mortar lined (DICL) pipes with different diameters are used as choices. The details of the pipes can be found in Wu et al. (2010a).

7.3.2 Case study objective function evaluation and assumptions

For calculating the total economic cost for the case study, only capital and operating costs of the network are considered. The capital cost results from the purchase and installation of network components (pipes and pumps) and the construction of pump stations. The pipe costs can be computed from the pipe data provided in Wu et al. (2010a). The cost of pumps and pump stations

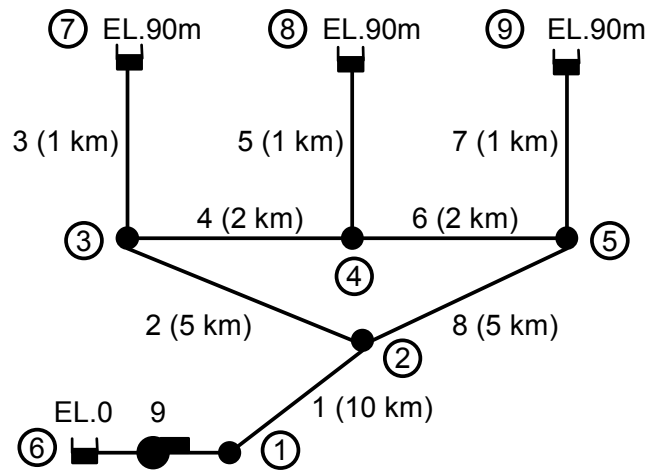


Figure 7.5 Case study network configuration [adapted from Wu et al. (2010a)]

can be estimated using the maximum power capacity of the pump (Wu et al., 2010a; Wu et al., 2010b), which is determined using the pump power estimation method based on the peak-day flow of the maximum demand during the design period. The peak-day flow is assumed to be 1.5 times the average-day flow based on the recommendation of the Water Services Association of Australia (2002) for populations over 10,000. In this study, the capital costs of VSPs include the costs of variable frequency drives (VFDs), which are taken as 10% of the pump cost (based on consultation with a number of experienced design engineers), and therefore are higher than the capital costs of FSPs.

The calculation of operating cost requires a demand forecasting model, the estimation of the annual energy consumption (AEC) [defined in Eq. (7.2)] and an electricity tariff forecasting model over the design period. Demand is dependent on both the average water consumption per capita and population size. In general, demand will increase as population grows. However, this might not be the case if policies aimed at reducing per capita demand are successful (Australian Bureau of Statistics, 2006). In order to avoid the introduction of unnecessary uncertainties into the optimization process and

emphasize the comparison between FSPs and VSPs, a constant annual water demand of 2,522,880 m³/year, corresponding to a peak-day flow of 120 L/s and an average-day flow of 80 L/s, is used for the case study. Therefore, the case study network is relatively small, supplying around 20,000 people. In addition, a design period of 100 years is used in this paper, which is consistent with the recommendation for the design of water mains by the Water Services Association of Australia (2002).

In estimating the AEC for FSPs, a flowrate determined using the proposed pump power estimation method based on the peak-day flow, is used. The exact value of this flowrate depends on the specific network configuration and will be just above the peak-day flow for which the FSPs are sized. This flowrate is considered to be able to provide a good estimate of the energy consumption associated with fixed-speed pumping for this case study. When VSPs are used, an EPS with four simulation periods is used to account for seasonal variations in demand during a year. During each of the four seasonal simulation periods, an average flowrate is used to estimate the energy consumption during that quarter of the year (values of 110L/s, 90L/s, 70L/s and 50L/s have been used to estimate the AEC for VSPs in this case study). As the same quantity of water is delivered, the actual annual pumping time for FSPs is less than that for VSPs. In addition, an average pipe roughness value of 0.25 mm over the entire design period (i.e. a pipe-aging model was not used) is used, as it has been found in a number of test runs that considering pipe aging by changing pipe roughness values over the design period does not have a significant impact on the results of WTS optimization accounting for cost and GHG emissions.

The average electricity tariffs (prices) in the retail market in Australia are determined by both wholesale prices and contract market prices, which are difficult to predict into the future (Electricity Industry Supply Planning Council, 2005). Saddler et al. (2004) suggested that in 30 years time, fossil fuels will still be the main source of electricity in Australia and that the prices of electricity generated by all fossil fuels will be higher. As a result, electricity tariffs are assumed to average \$0.14 per kWh (estimated by averaging on-peak

and off-peak values in South Australia) at the beginning of the design period and to increase at 3% per annum from the second and subsequent years of the design period.

Motor efficiency and pump efficiency are also required to calculate the AEC, as shown in Eq. (7.2). In this study, an average motor efficiency of 95% and an average pump efficiency of 85% are assumed. VSPs also have variable frequency drives (VFDs). Burt et al. (2006) found that although the efficiency of VFDs depends on the type of VFD, VFD rotational speed and VFD load, for all of the VFDs tested, efficiency was higher than 97% at full loads, and for some types of VFDs, the efficiency was higher than 99%. The study indicated that even at lower loads, efficiencies did not fall below 95%. This finding is in agreement with the information cited by Rooks and Wallace (2003): for large pumps (greater than 100 horse power or 74.6 kW), the efficiency of VFDs is generally greater than 95% when the speed is higher than 75%. As a result, a VFD efficiency of 95% is used in this case study. Finally, in the PVA that converts the operating costs in each year to their present values, a discount rate of 8% is used, which is a value commonly used by many water utilities in Australia.

In calculating total GHG emissions, only capital and operating GHG emissions of the network are considered, as mentioned previously. In this study, capital emissions are predominantly from pipe manufacture, as this represents the largest proportion of the impact (Filion et al., 2004). In calculating the embodied energy of the DICL pipes used in this study, a specific value of the embodied energy of 40.2 MJ/kg is used. This value was estimated by Ambrose et al. (2002) based on a combination of published and actual factory manufacturing data. In calculating capital emissions, an average emission factor of 0.98 kg CO₂-e/kWh is used, which is the full-fuel-cycle emission factor value of South Australia in 2007 (The Department of Climate Change, 2008).

The annual operating emissions are taken as the *AEC* multiplied by the projected average emission factor of the corresponding year. In this study, an

average emission factor of 0.98 kg CO₂-e/kWh is used for the first year of the design period. Thereafter, the emission factor is assumed to decrease linearly to 70% of the 2007 level at the end of the design period of 100 years due to Government policies of encouraging clean energy. This assumption is based on the Australian Government's commitment to reduce GHG emissions by at least 5% below 2000 levels by 2020 (The Department of Climate Change, 2010). It should be noted that there are many uncertainties involved in projecting emission factors, particularly for a long time period, such as 100 years. The operating emissions due to pumping also occur over time during the design period, however, no discounting (that is a discount rate of zero percent) has been applied to the calculation of pumping GHG emissions based on the recommendation of the Intergovernmental Panel on Climate Change (IPCC) (Fearnside, 2002).

7.3.3 Case study solution evaluation

The FCV based pump power estimation method is used to estimate the maximum pump capacity and energy consumption for this case study. For Step 1 in Figure 7.4, a flow of 1.5 times the peak-day flow is used as the threshold flow. This value is also used as the upper bound Q_u [Eq. (7.5)] for maximum pump power estimation and energy consumption estimation. The lower bound Q_l [Eq. (7.5)] is set to a target flow, which depends on specific case study assumptions and what the pump power is estimated for. For this case study, for estimating the maximum pump capacity of both VSPs and FSPs the peak-day flow is used as the target flow. For estimating the AEC of VSPs, the seasonal average-day flow is used as the target flow; whereas for estimating the AEC of FSPs, the peak-day flow is used as the target flow. Consequently, the vector \mathbf{Q}_a [Eq. (7.6)] contains the actual flows in pipes 3, 5, 7 (see Figure 7.5) that a particular system (a pipe network with a particular FCV setting) delivers; while the vector \mathbf{Q}_r [Eq. (7.7)] contains the required flows in the pipes, which is defined as one third of the target flow.

A tolerance of 0.5 L/s is used in the false position method based FCV setting search algorithm for this case study. Therefore, the FCV setting search optimization is considered to have converged if the objective function value g [Eq. (7.4)] is less than 0.5 L/s. For the particular optimization problem presented in this paper, it takes around two to five iterations for the false position method to converge. In addition, a stochastic optimization algorithm, such as a genetic algorithm, cannot guarantee that the final solutions are Pareto-optimal. Therefore, for the genetic algorithm runs conducted in this study, a total of 100 random seeds (i.e., random starting positions) have been used to ensure near-globally optimum solutions are found. As a result, the optimal fronts presented in this paper are formed using the best values obtained from the 100 runs.

7.4 Optimization results and discussion

The Pareto-optimal fronts obtained from the optimization runs using VSPs and FSPs are plotted in Figure 7.6. Eight typical solutions from the Pareto-optimal fronts are selected in this section to compare the optimization results obtained using VSPs and FSPs. These eight solutions are sorted according to the costs of the pipe networks and numbered consecutively from 1 to 8. Network 1 is the least-cost network and Network 8 is the highest-cost network. The pipe information for these eight networks is summarized in Table 7.1. The costs, GHG emissions and actual annual pumping hours of these networks with either variable- or fixed-speed pumping are presented in Table 7.2. The breakdown of the total cost and GHG emissions of these solutions is plotted in Figure 7.7.

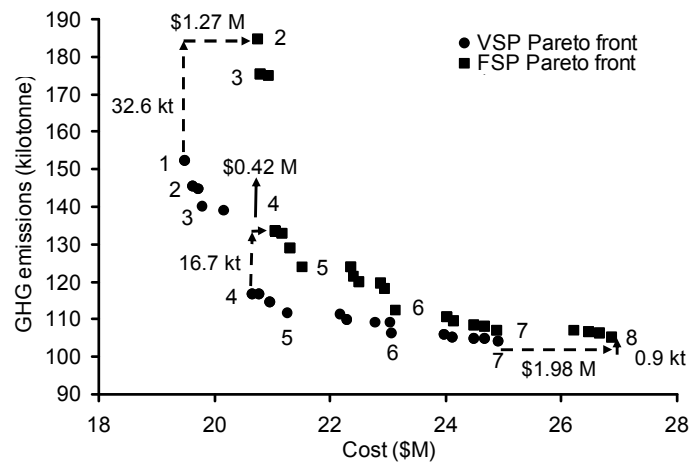


Figure 7.6 Comparison of Pareto-optimal fronts obtained using variable-speed pumping (VSP) and fixed-speed pumping (FSP) (Networks 2 to 7 are identical in pipe configuration for FSP and VSP systems)

It can be seen from both Figure 7.6 and Table 7.2 that six out of the eight networks (Networks 2 to 7) are on both the Pareto-optimal fronts obtained using variable- and fixed-speed pumping. However, the total cost and GHG emissions of the networks obtained using variable-speed pumping are much lower than those obtained using fixed-speed pumping. For example, the total cost of Network 4 with variable-speed pumping is 20.65 million dollars in contrast to 21.07 million dollars when fixed-speed pumping is used. In addition, the use of variable-speed pumping leads to a 16.7 kilotonne (kt), or 12.5%, saving in GHG emissions compared to the case when fixed-speed pumping is used.

Table 7.1 Pipe information of selected Pareto-optimal solutions

Network No.	Pipe 1	Pipe 2	Pipe 3	Pipe 4	Pipe 5	Pipe 6	Pipe 7	Pipe 8	Pipe Cost (\$M)	Pipe GHG (kt)
	Dia. (mm)	Dia. (mm)	Dia. (mm)	Dia. (mm)	Dia. (mm)	Dia. (mm)	Dia. (mm)	Dia. (mm)		
1	300	225	150	100 ^a	150	300	150	300	13.20	17.9
2	300	300	225	300	225	100	225	225	13.58	18.6
3	300	225	225	100	225	375	225	300	14.07	19.2
4	375	225	225	100	225	300	225	300	16.03	21.4
5	375	300	225	225	300	225	225	300	16.98	23.1
6	450	300	225	225	300	225	225	300	19.18	26.0
7	450	300	300	100	375	375	300	375	21.27	28.5
8	525	300	300	100	375	375	300	375	23.46	31.5

^aThe designs with the 100 mm pipe are not necessarily suitable solutions when considering network reliability.

Table 7.2 Costs and GHG emissions of selected solutions using variable- and fixed-speed pumps

Network No.	Variable-Speed Pumping						Fixed-Speed Pumping					
	Total Cost (\$M)	Total GHG (kt)	Annual Pumping Energy (10^3 kWh)	Pumping Cost (\$M)	Pumping GHG (kt)	Actual Annual Pumping Hours	Total Cost (\$M)	Total GHG (kt)	Annual Pumping Energy (10^3 kWh)	Pumping Cost (\$M)	Pumping GHG (kt)	Actual Annual Pumping Hours
1	19.49	152.1	1,610	4.47	134.1	8,675	NA	NA	NA	NA	NA	NA
2	19.63	145.6	1,524	4.23	126.9	8,084	20.76	184.7	1,994	5.54	166.1	5,400
3	19.80	140.1	1,452	4.03	120.9	8,521	20.81	175.1	1,872	5.20	155.9	5,686
4	20.65	116.7	1,145	3.18	95.4	8,084	21.07	133.4	1,344	3.73	112.0	5,400
5	21.27	111.7	1,064	2.95	88.6	8,336	21.54	123.7	1,208	3.35	100.6	5,546
6	23.06	106.2	963	2.67	80.2	8,336	23.15	112.2	1,035	2.87	86.2	5,546
7	24.91	104.2	909	2.52	75.7	8,486	24.90	106.9	942	2.61	78.4	5,640
8				NA			26.89	105.1	883	2.45	73.5	5,640

^aNote: Networks 2 to 7 are identical in pipe configuration for VSP and FSP systems; NA = Not Applicable.

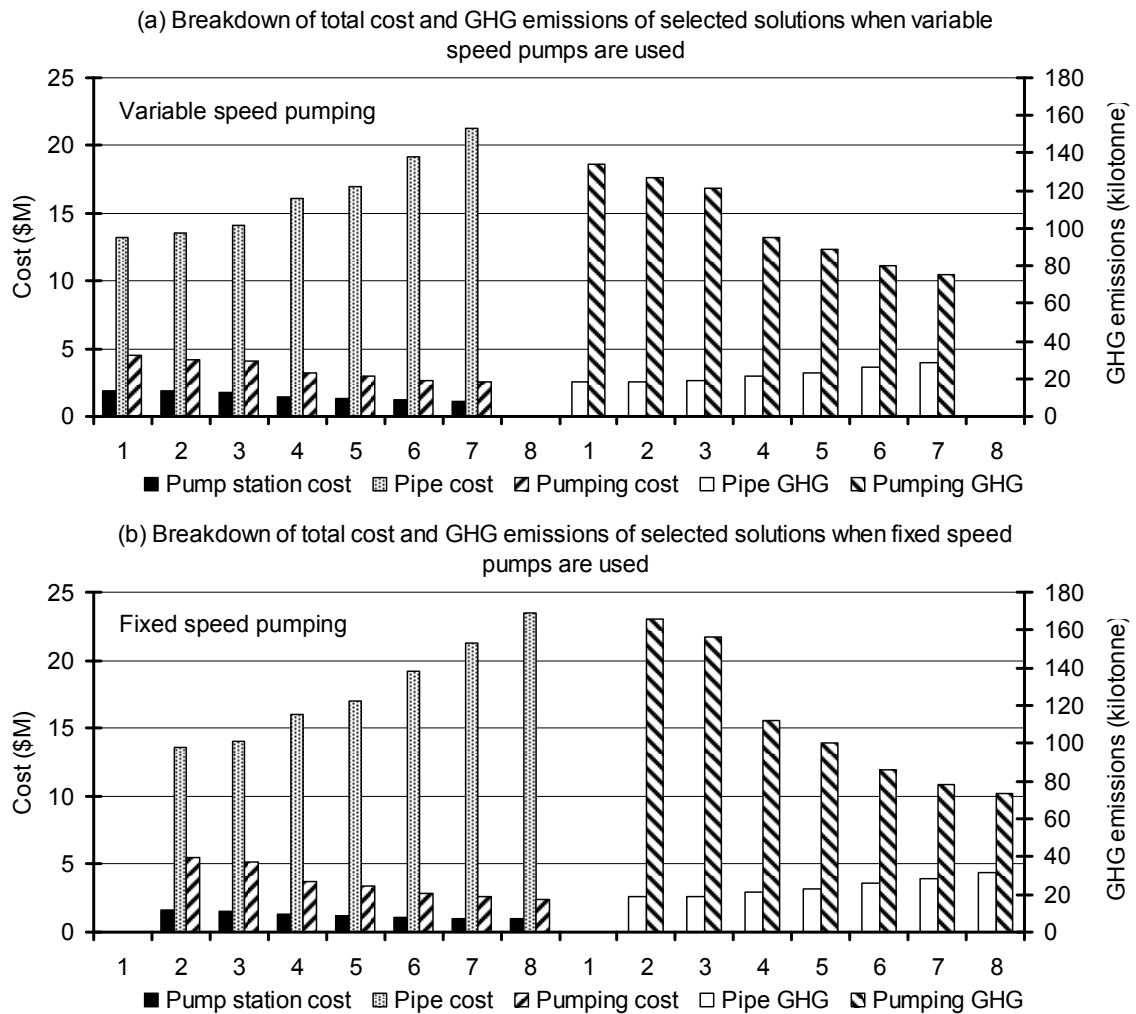


Figure 7.7 Breakdown of life cycle cost and GHG emissions of selected solutions with variable-speed pumping [plot (a)] and fixed-speed pumping [plot (b)]

Figure 7.6 also shows that both Pareto-optimal fronts obtained using FSPs and VSPs converge to a single GHG emission level of approximately 100 kt at the low emission end of the horizontal axis. This is because the solutions on the right hand side of the optimal front are solutions with large pipes and high capital costs. For these solutions, the friction losses in the pipes are so low that the operating energy consumption is mainly dependent on the static head (determined by the elevation difference between the water source and storage tanks). In other words, the effectiveness of replacing FSPs with VSPs in reducing operating costs and emissions by reducing friction losses within the system is more significant for smaller pipe diameter systems with higher dynamic heads (friction losses) relative to static heads.

It is also observed that use of VSPs leads to smaller optimal networks that are both cheaper in terms of economic cost and GHG emissions. For example, the lowest-cost network on the far left end of the Pareto-optimal front obtained using variable-speed pumping (Network 1) has a pipe cost of 13.20 million dollars (see Table 7.1), while the lowest-cost network obtained using fixed-speed pumping (Network 2) has a pipe cost of 13.58 million dollars. In previous research, it has been found that when FSPs are used, smaller networks often have higher GHG emissions compared to larger networks due to the higher friction losses in pipes with smaller diameters (Wu et al., 2010b). However, this is not the case when different types of pumps are used. For example, Network 1 with variable-speed pumping generates 32.0 kt less GHG emissions due to pumping compared with Network 2 with fixed-speed pumping, resulting from reduced annual energy consumption (Table 7.2 and Figure 7.7). In addition, the capital emissions of Network 1 are lower than those of Network 2 (Table 7.1 and Figure 7.7). As a result, Network 1 with variable-speed pumping generates 32.6 kt less GHG emissions compared to Network 2 with fixed-speed pumping. The reason for this is that the effect of increased friction loss on operating energy consumption due to reduced pipe diameters in smaller networks is less significant than the effect of increased friction losses due to increased flowrate (resulting from the use of FSPs).

For the same reason, the least-GHG emission solution obtained using variable-speed pumping (Network 7) emits 0.9 kt less GHG emissions than the least-emission solution obtained using fixed-speed pumping (Network 8), even though Network 8 uses pipes with larger diameters compared with Network 7. Similar results can be obtained from analyzing the breakdown of total costs, but the difference between the costs of the two least-cost solutions or the two least-emission solutions obtained using different types of pumps is not significant due to the effect of the 8% discount rate used in the PVA.

In addition, the fact that the same solutions exist in the middle regions of both optimal fronts shows that the choice of using a FSP or VSP mainly alters the solutions at the two extreme ends of the optimal front. This demonstrates the advantage of the proposed generic pump power estimation method over the approach used in previous studies, where a number of commercially available FSPs have been used as decision variables (Wu et al., 2010a; Wu et al., 2010b). Because the operating range of a specific pump may not suit every single potential network solution in the optimization process, some network configurations are favored by the use of certain pumps, which results in an unfair comparison in the optimization process. For example, a FSP which suits a sharp system curve (with small flow and high head) may not perform well when connected to a system with large pipes whose system curve is flatter (with lower total head due to lower friction losses). Thus, the selection process within the optimization may be biased towards smaller networks with high friction loss and large networks with less friction losses may be disadvantaged.

7.5 Conclusions

In this study, a generic pump power estimation method has been developed in order to incorporate variable-speed pumping into the conceptual design or planning of water transmission systems (WTSs) using optimization with multiple flow constraints, so that the costs and GHG emissions for a new

WTS associated with pumping can be minimized. This pump power estimation method makes use of a flow control valve (FCV) and can be implemented using a hydraulic solver, such as EPANET, through a false position method based single-objective optimization approach.

In this study, a case study is used to demonstrate the application of the proposed pump power estimation method and investigate the impact of variable-speed pumping on the optimization of WTSs accounting for both total cost and GHG emissions. It has been found that the use of VSPs can reduce both the total cost and GHG emissions of the optimal solutions for a WTS. The effectiveness of replacing FSPs with VSPs in reducing operating costs and emissions is more significant for a smaller pipe diameter system with higher dynamic heads (friction losses) relative to static heads. As a result, compared with FSPs, use of VSPs leads to smaller network solutions which are both cheaper in terms of cost and GHG emissions. Therefore, switching from fixed-speed pumping to variable-speed pumping can be an effective method for reducing total cost and GHG emissions of WTSs when used in conjunction with multiobjective optimization.

The proposed pump power estimation method employs a generic pump concept, which enables pump power to be adjusted easily according to the characteristics of each specific network configuration generated in the optimization process. This feature avoids possible distortions resulting from a specific pump curve being introduced into the optimization process, enabling a fair comparison between different network configurations to be achieved.

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Chapter 8

Sensitivity of optimal tradeoffs between cost and greenhouse gas emissions for water distribution systems to electricity tariff and generation

Publication 4

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Wu, W. (Candidate)

Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.

I hereby certify that the statement of contribution is accurate.

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Research supervision and manuscript evaluation.

I hereby certify that the statement of contribution is accurate and I give permission for the inclusion of the paper in the thesis.

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Abstract

Increased awareness of climate change has shifted the focus of water distribution system (WDS) optimization research from cost minimization only to the incorporation of energy or associated greenhouse gas (GHG) minimization. In this study, a sensitivity analysis is conducted to investigate the impact of electricity tariff and generation (emission factors) on the results of multiobjective WDS optimization accounting for both total economic cost (both capital and operating costs) and GHGs. A multiobjective genetic algorithm based optimization approach is used to conduct the analysis. The results show that electricity tariff has a significant impact on the total economic cost of WDSs and the selection of optimal solutions. In contrast, the changes of emission factor into the future have a significant impact on the total GHGs from WDSs. However, it does not alter the final solutions on the Pareto-optimal front.

8.1 Introduction

Increased awareness of climate change has shifted the focus of water distribution system (WDS) optimization research from cost minimization only to the incorporation of energy minimization or associated greenhouse gas (GHG) minimization. The first study considering the direct impacts of WDSs on global warming was conducted by Dandy et al. (2006), in which a single-objective approach was used to minimize the material usage and associated GHG emissions from WDSs. Subsequent studies investigated the optimal tradeoffs between GHG emissions and life cycle economic costs of WDSs (Wu et al., 2008b) and the impact of discount rate on these tradeoffs by using a multiobjective optimization approach (Wu et al., 2010b). In the same year, Wu et al. (2010a) explored the impact of carbon pricing on the single- and multi-objective optimization of WDSs accounting for GHG emissions. In related work, Herstein et al. (2009a) included an environmental index as one of the objectives of a multiobjective WDS optimization problem, which is a single parameter consisting of measures of resource consumption, environmental discharges (including GHG emissions) and environmental impacts. In another study, Ghimire and Barkdoll (2010) found that reduction in water demand, main pump horsepower, and booster horsepower can lead to significant energy savings from operations of WDSs.

While previous optimization studies have identified that there are significant tradeoffs between total costs and GHG emissions, they have not explored the sensitivity of these tradeoffs to such issues as electricity tariff and emissions associated with electricity generation. This is mainly because currently most water utilities and energy producers operate independently and water utilities have little control over electricity tariff and generation. However, the water and energy industries are closely related: a large amount of water is needed for energy production and a large amount of energy is needed for treatment, transmission and distribution of water. This paper explores the water - energy nexus and its impact on the tradeoffs between cost and GHG emissions from WDSs. As part of the sensitivity analyses conducted in this paper, realistic

ranges of the above two factors are considered based on data from Australia. In total, two different scenarios including five different combinations of the two factors are considered.

8.2 Problem formulation

8.2.1 Case study description

A water transmission network (Figure 8.1) is used as the example network for this study. A similar network configuration has been investigated in previous studies that have considered optimal tradeoffs between cost and GHG emissions (Wu et al., 2010a). The required flows to the three storage reservoirs are assumed to be the same (i.e. one third of the total water demand). The water levels in the storage reservoirs are assumed fixed and under the control of local water utilities. It is also assumed that the storage reservoirs are appropriately sized to meet different loading cases, such as fire flow and emergencies. Pipe sizes are considered as decision variables and ductile iron cement mortar lined (DICL) pipes are used. Detailed information of the pipes and network can be found in Wu et al. (2010a).

8.2.2 Objective function evaluation

The problem considered in this paper is formulated as a multiobjective WDS design optimization problem, in which two objectives are used: the minimization of the total economic cost of the system and the minimization of the total GHGs emitted from the system. The formulation used in this study is similar to the one presented in Wu et al. (2010b). The difference is that instead of using real fixed-speed pumps as decision variables in the optimization process, as has been done in previous studies (Wu et al., 2010a; Wu et al., 2010b), the pump power estimation method developed in Wu et al. (2012b) is used to estimate the maximum pump capacity and the annual

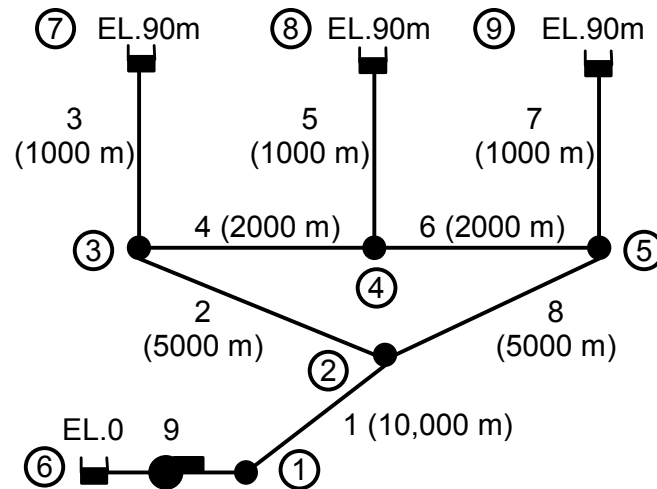


Figure 8.1 Case study network configuration [adapted from Wu et al. (2010a)]

energy consumption (AEC) in kWh for calculation of operating costs and emissions. For further details regarding the objective function evaluation process, refer to Wu et al. (2010b) and Wu et al. (2012b).

8.3 Factors considered in sensitivity analysis

In this study, three options for each of the two factors are considered based on uncertainties or possible government strategies into the future. The assumptions for the two factors are based on Australia, and presented in the following two subsections and are for illustration purposes only. However, the methodology presented here is generally applicable to other locations by using local conditions. At the end of this section, the two optimization scenarios considered in the sensitivity analysis are summarized.

8.3.1 Electricity tariffs

The average electricity tariffs (prices) in the retail market in Australia are determined by both wholesale prices and contract market prices (Electricity Industry Supply Planning Council, 2005). The average electricity wholesale prices have been relatively constant since the introduction of the National Electricity Market in 1998, but have increased significantly after 2007 due to high demand and tight supply (Australian Bureau of Agricultural and Resource Economics, 2008). In contrast, the electricity prices in the contract market are difficult to predict. Saddler et al. (2004) suggested that in 30 years time, brown and black coal will still be the main sources of electricity in Australia and that the prices of electricity generated by all fossil fuels will be significantly higher. Therefore, three future electricity tariff options are assumed in this study, as shown in Figure 8.2. For these options, electricity tariffs are assumed to average \$0.14 per kWh at year one, which is estimated by averaging on-peak and off-peak values, and to increase at $e=+1.5\%$ per annum (pa) (option 1), $e=+3\%$ pa (option 2) and $e=+4\%$ pa (option 3), respectively.

8.3.2 Electricity generation

In this paper, the impact of electricity generation on GHG emissions is considered via the use of emission factors, which are the kilograms of CO₂-e (carbon dioxide equivalent) emitted per kWh electricity purchased by end electricity users (The Department of Climate Change, 2008). The value of emission factors depends on the mix of the sources of electricity, such as combustion of fossil fuel, nuclear energy, solar energy or hydroelectric energy, and may change over time and across regions. In this paper an annual average value is used for the sensitivity analysis. This average value is considered to change over time resulting from changes in the mix of energy sources due to a government's response to global warming, for example. The UN Intergovernmental Panel on Climate Change (IPCC) advises developed

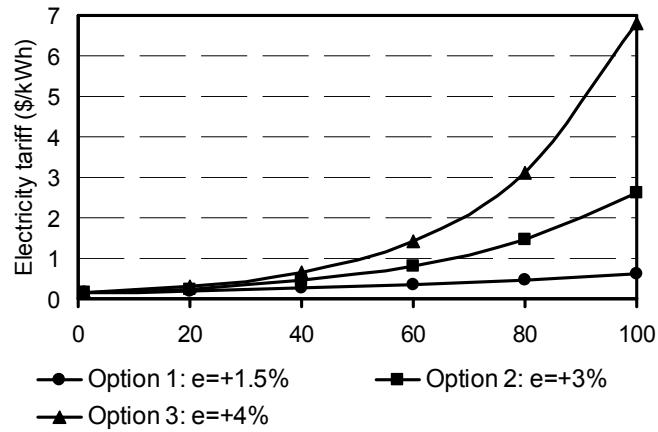


Figure 8.2 Three electricity tariff options considered over 100 years (e = electricity tariff change per annum)

countries to cut their carbon emissions by 25–40% of 1990 levels by 2020 to avoid catastrophic impacts due to climate change. The Federal Government of Australia has committed to carbon reduction by reducing carbon emissions by at least 5% of 2000 levels by 2020 (The Department of Climate Change, 2010). A linear interpolation of this target will result in over 25% reduction of carbon emissions of 2007 levels in 100 years. However, it is difficult to project long term emission factor values. Consequently, three hypothetical options are used in this study based on previous full fuel cycle emission factor values for South Australia (The Department of Climate Change, 2008) and assumptions made in relation to Government policies.

According to The Department of Climate Change (2008), the emission factor of electricity in South Australia has been decreasing since 2000. However, according to the Australian Bureau of Agricultural and Resource Economics (2008), the generation of electricity in Australia will not be able to transfer into renewable sources quickly within the next 30 years. Consequently, coal, gas and oil are likely to remain the major sources of electricity in Australia.

Therefore, the first option is assumed to be a constant emission factor equal to the 2007 value, which is 0.98 kg CO₂-e per kWh (The Department of Climate Change, 2008). This option is mainly used as a baseline option for comparison purposes. The second option is based on the assumption that the Australian Government is able to reduce GHG emissions by at least 5% below 2000 levels by 2020 (The Department of Climate Change, 2010); as a result, the emission factor will reduce by $e_m = -30\%$ (to 70% of 2007 levels) by the year 2106 (100 years from 2007). The third option is based on the assumption that the Australian Government is committed to reinforcing tough GHG reduction policies and therefore, the emissions from electricity production will be reduced by $e_m = -60\%$ (to 40% of 2007 levels) in a 100 year period. For both options 2 and 3, a linear reduction is assumed, as shown in Figure 8.3.

8.3.3 Optimization scenarios and combinations of factors considered

In order to test the sensitivity of the optimization results to the two factors described above, two optimization scenarios, each dedicated to one of the factors, are considered. In each of the two optimization scenarios, one factor is varied and the remaining factor is set at the moderate value of the three options considered [e.g. option 2 for electricity tariff ($e = +3\%$ pa) and emission factor ($e_m = -30\%$ by year 100)]. This leads to a total of five combinations of the two factors, which are shown in Table 8.1.

8.4 Multiobjective GA optimization

In this study, a multiobjective genetic algorithm called WSMGA (Water System Multiobjective Genetic Algorithm) (Wu et al., 2010b) is used to solve the multiobjective WDS optimization problem. In WSMGA, an integer coding scheme is used to account for the discrete decision variables (pipe sizes), the EPANET2 hydraulic solver is used to simulate network behavior, and a pump

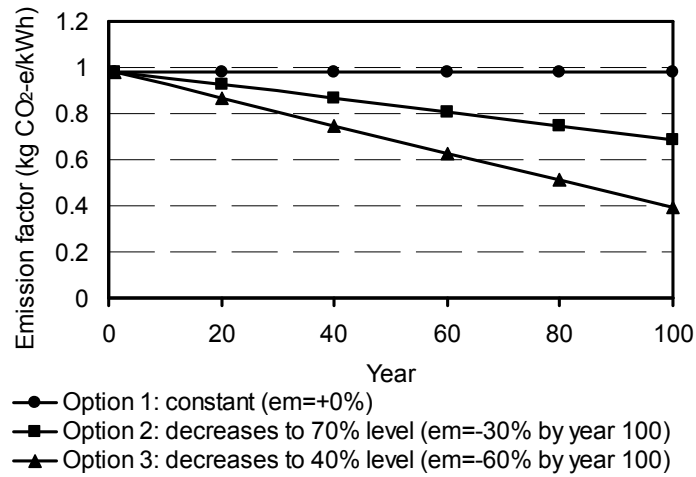


Figure 8.3 Three emission factor options considered over 100 years (em = total emissions reduction over 100 years)

Table 8.1 Optimization scenarios and combinations of factors investigated as part of the sensitivity analysis

Optimization scenario	Factor combination	Electricity tariff option (e value)	Emission factor option (em value)
Electricity tariff (e)	A	1 (+1.5%)	2 (-30%)
	B	2 (+3.0%)	2 (-30%)
	C	3 (+4.0%)	2 (-30%)
Emission factor (em)	D	2 (+3.0%)	1 (+0%)
	B	2 (+3.0%)	2 (-30%)
	E	2 (+3.0%)	3 (-60%)

power estimation method developed by Wu et al. (2012b) is used to estimate the maximum pump capacity and energy consumption for each solution network. For details of the solution evaluation process incorporating the pump power estimation method, refer to Wu et al. (2012b). Details of the GA parameters settings are given in Wu et al. (2010a, b).

8.5 Sensitivity analysis results

The results from the multiobjective GA runs for each of the combination of factors investigated (see Table 8.1) are plotted in Figure 8.4. Each plot in Figure 8.4 shows the optimization results from one optimization scenario (each including three factor combinations) (see Table 8.1). The network configurations of four typical optimal designs from the Pareto-optimal fronts presented in Figure 8.4 are summarized in Table 8.2. The selected designs are sorted according to total pipeline cost, which is a function of the sizes of the pipes selected: the higher the design number, the more expensive the pipeline. The numbers next to the solution points in Figure 8.4 correspond to the design numbers in Table 8.2. In addition, the breakdown of the total cost and emissions of these solutions is summarized in Table 8.3. Detailed results from the sensitivity analysis are presented in the following two subsections.

8.5.1 Impact of electricity tariff

The electricity tariff used has an impact on the total cost of the network. Table 8.3 shows that a more rapidly increasing electricity tariff (e.g. $e = +4.0\%$) into the future will increase operating costs considerably, which in turn increases total costs as shown in Figure 8.4(a). In addition, electricity tariff may also alter the solutions on the optimal front. Figure 8.4(a) shows that a higher electricity cost into the future removes some networks with higher GHG emissions from the optimal front. Design 1 is one such example. However, the three different electricity tariff options considered lead to networks with

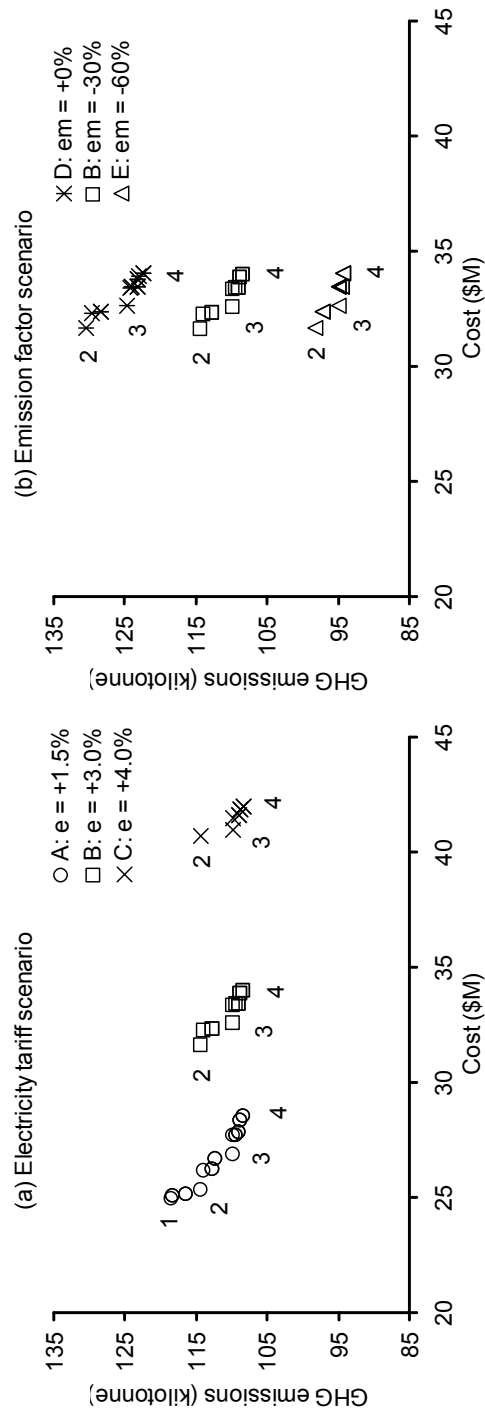


Figure 8.4 Optimization results from the two scenarios (all optimal designs with same numbers in both plots have exactly the same pipe configurations)

Table 8.2 Pipe information of the six typical Pareto-optimal designs

Design number	Pipe diameters (m)								Pipe cost (\$M)
	Pipe 1	Pipe 2	Pipe 3	Pipe 4	Pipe 5	Pipe 6	Pipe 7	Pipe 8	
1	375	225	225	100 ^a	225	300	225	300	16.0
2	375	300	225	225	300	225	225	300	17.0
3	450	300	225	225	300	225	225	300	19.2
4	450	300	300	100 ^a	375	375	300	375	21.3

^aThe designs with the 100 mm pipe are not necessarily suitable solutions when considering network reliability.

Table 8.3 Breakdown of total cost and GHG emissions of the selected solutions obtained from the two optimization scenarios (e = electricity tariff increase per annum and em = emission factor change over 100 years)

Optimisation scenario	Factor combination	Design number	Pip cost (\$M)	Pump station cost (\$M)	Operating cost (\$M)	Total cost (\$M)	Pipe GHG (kt)	Operating GHG (kt)	Total GHG (kt)	
Electricity tariff scenario (em=-30%)	A (e=+1.5%)	1	16.0	1.4	7.6	25.0	21	97	118	
		2	17.0	1.3	7.1	25.4	23	91	114	
		3	19.2	1.2	6.5	26.9	26	84	110	
		4	21.3	1.1	6.2	28.6	28	80	108	
	B (e=+3.0%)	2	17.0	1.3	13.4	31.6	23	91	114	
		3	19.2	1.2	12.3	32.6	26	84	110	
		4	21.3	1.1	11.7	34.1	28	80	108	
		2	17.0	1.3	22.4	40.7	23	91	114	
	C (e=+4.0%)	3	19.2	1.2	20.6	40.9	26	84	110	
		4	21.3	1.1	19.6	42.0	28	80	108	
		2	17.0	1.3	13.4	31.6	23	107	130	
		3	19.2	1.2	12.3	32.6	26	99	125	
D (em=+0%)	4	21.3	1.1	11.7	34.1	28	94	122		
	Emission factor scenario (e=+3.0%)	B (em=-30%)	2	17.0	1.3	13.4	31.6	23	91	114
			3	19.2	1.2	12.3	32.6	26	84	110
		E (em=-60%)	4	21.3	1.1	11.7	34.1	28	80	108
2			17.0	1.3	13.4	31.6	23	75	98	
3			19.2	1.2	12.3	32.6	26	69	95	
4	21.3	1.1	11.7	34.1	28	66	94			

similar configurations and GHG emissions within a similar range (105 to 120 kilotonnes). In addition, for the same network configuration, the electricity tariff option selected has no impact on the total GHG emissions of the network, as shown in Table 8.3.

8.5.2 Impact of electricity generation

The emission factor appears to have little impact on the configuration of the selected optimal networks, as similar solutions within the same cost range are obtained using the different emission factor options [Figure 8.4(b)]. In addition, the emission factor used has no impact on total network cost. Table 8.3 shows that the same pipe configuration has the same pipe cost, pump station cost and operating cost, irrespective of which emission factor option is used.

In contrast, the emission factor has a significant impact on the total GHG emissions from the system over the design period. It can be seen from Figure 8.4(b) and Table 8.3 that a gradual reduction in the emission factor to 40% of the year zero level in year 100 ($em = -60\%$) could reduce the total GHG emissions from WDSs by more than 23%. This is because the gradual 60% decrease in emission factor in 100 years reduces the operating emissions by around 30%, as shown in Table 8.3. The 30% gradual reduction in emission factors ($em = -30\%$) over 100 years can reduce the total GHG emissions of the system by 14% and reduce the operating emissions of the system by almost 18%.

8.5.3 Discussion

The results obtained indicate that changes in electricity tariffs into the future can change the composition of the total cost significantly, which also alters the tradeoffs between the two objectives and results in different final optimal solutions. In contrast, as the reduction in emission factors into the future

occurs more gently, the primary impact is to scale down the total emissions of the optimal solutions. In addition, the selection of the design life may also have an impact on the optimization results. A shorter design horizon, such as 50 years or shorter, will reduce future impact of WDSs (represented by operating costs and emissions). This may reduce the tradeoffs between the two objectives, which will favor networks with smaller capital costs but higher GHG emissions. However, a long design horizon, such as 100 years, makes accurate projection of electricity tariffs and emission factors into the future difficult due to high levels of uncertainties.

It should be noted that the case study considered is a water transmission network, which are relatively simple compared with water distribution networks, which often have hundreds of pipes. However, it is likely that the impact of electricity tariffs and emission factors on the objective function evaluation process and final optimization results obtained for the case study considered in this paper can be generalized to WDS. In addition, the approach presented in this study is general and can be applied to both water transmission networks and water distribution networks with varying complexity.

8.6 Summary and conclusions

In this paper, the sensitivity of the optimal tradeoffs between cost and GHG emissions to electricity tariff and generation are assessed for a case study water transmission network. As part of the sensitivity analysis, two optimization scenarios, including five combinations of the two factors investigated, were considered.

The optimization results show that electricity tariffs have a significant impact on the total cost of WDSs, but little impact on the total GHG emissions from a particular network. However, higher electricity tariffs into the future can remove networks with higher emissions from the Pareto-optimal front, which

potentially leads to a final WDS with lower GHG emissions. This indicates that GHG emissions from WDSs can be further reduced by managing the water and energy industries jointly. In contrast, emission factors have no direct impact on the total cost of WDSs. However, emission factors into the future have a significant impact on the total GHG emissions that will be generated by the system. A 60% gradual reduction of emission factor during a 100 year period can reduce the operating GHG emissions of the system by 30% and the total emissions by over 23%.

8.7 Acknowledgements

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Chapter 9

Surplus power factor as a resilience measure for assessing hydraulic reliability in water transmission system optimization

Publication 5

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Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.

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Abstract

The hydraulic reliability of a water distribution system (WDS) can be improved by increasing the resilience to failure conditions. In previous research, numerous measures have been developed to quantify network resilience which has been consequently linked to the hydraulic reliability of WDSs. Often, the difference between the output pressure head and the minimum required pressure head is required in the calculation of these network resilience measures. Difficulties arise when these measures are applied to water transmission systems (WTSs). The reason for this is that in a WTS, water is often pumped into a storage tank or reservoir, in which case the difference between the output pressure head and the minimum required pressure head is always zero. In order to overcome this shortcoming, it is suggested that the surplus power factor can be used as a network resilience measure, as calculation of this measure does not require the pressure value at the outlet of a WDS. In the research presented here, three case studies are used to assess the suitability of the surplus power factor as a network resilience measure for WDSs. A fourth case study is used to demonstrate the application of surplus power factor as a network resilience measure for WTSs, to which the other measures cannot be applied. The results show that the surplus power factor can be used as a network resilience measure to incorporate hydraulic reliability considerations into the optimization of WDSs and particularly WTSs.

9.1 Introduction

Hydraulic reliability is an important performance measure of water distribution systems (WDSs), as it refers directly to their basic function (Ostfeld et al., 2002). It is therefore often considered as the ultimate goal of WDS design (Li et al., 1993). However, there is no universally accepted approach for assessing the reliability of WDSs (Mays, 1996). A common way of characterizing the hydraulic reliability of WDSs is by measuring “how far” a system is from failure. The greater the excess capacity of a system in relation to a specified hydraulic failure condition, the more resilient the system is to hydraulic failures, thereby improving the hydraulic reliability of the system. It should be noted that this definition of hydraulic reliability is different from measures of reliability that refer to the probability of non-failure of WDSs (Tolson et al., 2004) and does not take account of mechanical failures, such as pipe breakage or the absence of alternative supply paths.

In previous research, a number of resilience-based hydraulic reliability measures have been developed for WDSs. As early as 1985, Gessler and Walski (1985) used the excess pressure at the worst node in the system as a benefit measure in a pipe network optimization problem to ensure sufficient water with acceptable pressure is delivered to demand nodes. Todini in 2000 developed a hydraulic reliability measure called the resilience index, which directly measures the ability of a network to overcome failure conditions. Other similar hydraulic reliability measures include the network resilience measure developed by Prasad and Park (2004); a robustness measure, as used in Kapelan et al. (2005) and Babayan et al. (2007); and the modified resilience index developed by Jayaram and Srinivasan (2008).

Difficulties arise when applying the above measures to water transmission systems (WTSs). This is because these measures have one thing in common – their calculation relies on the difference between the required and minimum allowed pressure heads at the outlet of the system, which are often zero in WTSs, as in such systems water is usually delivered into tanks or reservoirs.

Thus, for WTSs, the values of the above measures are always zero. As a result, explicit consideration of hydraulic reliability as a design objective of WTSs remains a challenge.

In 2006, Vaabel et al. (2006) introduced the surplus power factor (s), which is based on the concepts of hydraulic power and energy transmission of flow in a pipe. The surplus power factor can be used to measure the network resilience of a hydraulic system subject to failure conditions simultaneously on the basis of both pressure and flow (Vaabel et al., 2006). More importantly, calculation of the surplus power factor does not require the value of the pressure head at the outlet of the system. Therefore, the surplus power factor is an ideal candidate for the calculation of the network resilience of WTSs.

In this research, the surplus power factor developed by Vaabel et al. (2006) is validated against three existing network resilience measures using three benchmark case studies. Then, a three-tank system is used to demonstrate the application of the surplus power factor as a network resilience measure for WTSs, to which the other measures cannot be applied, as discussed above.

9.2 Surplus power factor (s)

The surplus power factor (s) was introduced by Vaabel et al. (2006) to evaluate the hydraulic power capacity of WDSs on the basis of both flow within pipes and pressure head at the inlets of pipes. In this research, the surplus power factor is also called the s factor for the sake of convenience.

For the system shown in Figure 9.1, Q_{in} and Q_{out} are the inflow and outflow of the pipe, respectively; H_{in} and H_{out} are the heads at the inlet and outlet of the pipe, respectively; h is the head loss within the pipe; and q is the flow within the pipe. The hydraulic power at the outlet of the pipe (P_{out}) can be calculated using the following equation (Vaabel et al., 2006):

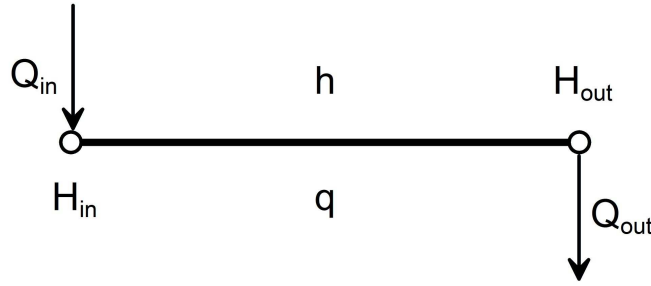


Figure 9.1 Flows, heads and head loss for a single pipe [adapted from Vaabel et al. (2006)]

$$P_{out} = \gamma(Q_{in} H_{in} - cQ_{in}^{a+1}) \quad (9.1)$$

where, γ is the specific weight of water; c is the pipe resistance coefficient (that depends on the form of the head loss equation used); and a is the flow exponent. The maximum hydraulic power at the outlet of the pipe P_{max} can be expressed using the following equation (Vaabel et al., 2006):

$$P_{max} = \frac{\gamma a}{c^a} \left(\frac{H_{in}}{a+1} \right)^{\frac{a+1}{a}} \quad (9.2)$$

Thus, the surplus power factor (s) is defined as:

$$s = 1 - \frac{P_{out}}{P_{max}} \quad (9.3)$$

or:

$$s = 1 - \frac{a+1}{a} \left[1 - \frac{1}{a+1} \frac{Q_{in}^a}{Q_{max}^a} \right] \frac{Q_{in}}{Q_{max}} \quad (9.4)$$

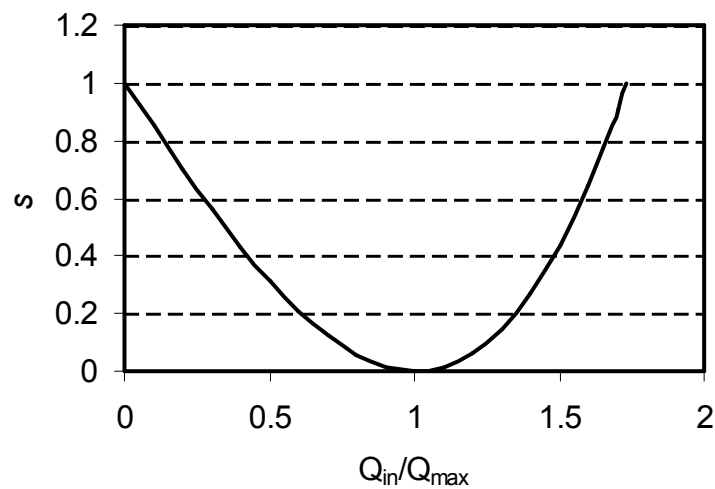


Figure 9.2 Surplus power factor s as a function of Q_{in}/Q_{max}

where, Q_{max} is the flow that gives the maximum hydraulic power at the outlet of the pipe. The surplus power factor can be used as a measure of the network resilience of a hydraulic system. The range of the s factor is from zero to 1, as plotted in Figure 9.2. When s is equal to zero, P_{out} equals P_{max} and the hydraulic system works at its maximum capacity. Under this condition, any leakage can result in failure of the system in terms of meeting the needs of end water users, such as delivering enough water with sufficient pressure. As the value of the s factor increases, the resilience of the system to failure conditions increases. However, as long as the system delivers water to end users, the value of s cannot reach 1, as when Q_{in}/Q_{max} reaches $\sqrt{3}$, the friction loss within the pipe will be equal to H_{in} and there will be no flow in the pipe. It should also be noted that in Figure 9.2, a given value of the s factor corresponds to two different values of Q_{in}/Q_{max} . While this is theoretically correct, when Q_{in} is greater than Q_{max} , very high input power values are required to achieve a certain s factor value, which results in extremely low efficiency within the system. Therefore, the condition of Q_{in}

being greater than Q_{\max} is not practical and can therefore be ignored for the purpose of estimating the network resilience of WDSs.

9.3 Case studies

A total of four case studies are investigated in this research. The first three case studies are used to assess the suitability of the surplus power factor as a network resilience measure. The last case study is used to demonstrate the application of the surplus power factor as a network resilience measure for a water transmission system (WTS), for which other network resilience measures cannot be used.

The first case study is a two-loop network, which was introduced in Abebe and Solomatine (1998), and then studied by Todini (2000) and Prasad and Park (2004). The details of this network can be found in Prasad and Park (2004). The second case study is the New York Tunnel (NYT) problem, which has been studied extensively by many researchers. Details of this problem can be found in Zecchin et al. (2006). The third case study is the Hanoi problem, which is also a WDS benchmark case study that has been considered by numerous authors. Details of this case study can also be found in Zecchin et al. (2006). The fourth case study is a three-tank WTS consisting of a water source, a pump, eight pipes and three storage tanks. Water needs to be delivered into the three tanks via a looped network. Details of this case study can be found in Wu et al. (2010a).

9.4 Validation results for the first three water distribution system case studies

In order to compare the utility of the surplus power factor as a measure of network resilience, The average s factor (s_{ave}) is compared with three

commonly used network resilience measures, including the minimum surplus head I_m (Gessler and Walski, 1985), the resilience index I_r (Todini, 2000) and the modified resilience index MI_r (Jayaram and Srinivasan, 2008) for the first three case studies introduced previously. Definitions of the three resilience measures are provided below:

1. *Minimum surplus head (I_m):* The minimum surplus head I_m is defined as the surplus pressure head at the worst node. This measure was used as a hydraulic benefit indicator in Gessler and Walski (1985), and then as a hydraulic reliability measure in Prasad and Park (2004).
2. *Resilience index (I_r):* The resilience index (I_r) developed by Todini (2000) is defined as the quotient of the difference between the actual output power and the required output power and the difference between the total input power and the required output power.
3. *Modified resilience index (MI_r):* The modified resilience index (MI_r) developed by Jayaram and Srinivasan (2008) is defined as the amount of surplus power available at the demand nodes as a percentage of the total minimum required power.

The actual configurations of the networks used for the comparison study are generated using a multiobjective optimization approach, in which the cost of the network is minimized and the network resilience represented by s_{ave} is maximized. The optimal fronts representing the tradeoffs between cost and s_{ave} for the three case studies are plotted in Figure 9.3. The values of the other three hydraulic reliability measures of these optimal solutions are also calculated. The number of optimal solutions investigated for each case study and the correlation between s_{ave} and the other three measures (I_m , I_r and MI_r) are summarized in Table 9.1. Values of the cost and network resilience measures of four typical solutions for each case study are summarized in Table 9.2. The numbers and square symbols in Figure 9.3 show the locations of these typical solutions on the corresponding Pareto-optimal front.

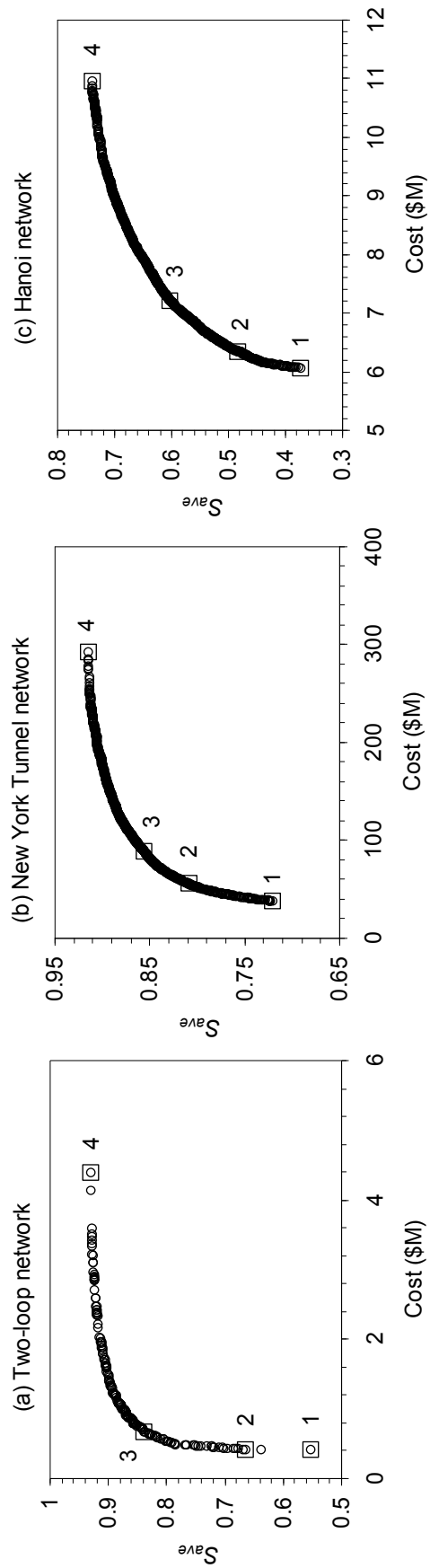


Figure 9.3 Pareto-optimal solutions of the first three case studies

Table 9.1 Correlation between average s factor and other three network resilience measures (I_m , I_r and MI_r) for the first three case studies

Network	Number of solutions	Correlation		
		s_{ave} and I_m	s_{ave} and I_r	s_{ave} and MI_r
Two-loop	186	0.94	0.97	0.97
NYT	737	0.75	0.82	0.82
Hanoi	962	0.93	0.97	0.97

It can be seen from Figure 9.3 that there are significant tradeoffs between the cost of the network and the network resilience level represented by s_{ave} for all three case studies. Often, a small increase in cost can result in significant increase in network resilience. Both Tables 9.1 and 9.2 show that s_{ave} is highly correlated with the other three network resilience measures. The correlation coefficients between s_{ave} and I_r , and between s_{ave} and MI_r are 0.97 for the two-loop and Hanoi networks. The correlation between s_{ave} and I_m is slightly lower. This is because s_{ave} , I_r and MI_r are all calculated based on the performance of the whole network, whereas, values of I_m are mainly affected by a number of critical nodes (one node for the two-loop network, one node for the Hanoi network and three nodes for the NYT problem). In addition, the correlation between s_{ave} and the other three measures for the NYT problem are slightly lower. Again, the reason for this is that the I_m , I_r and MI_r values for the NYT problem are controlled by three critical nodes.

Table 9.2 Typical solutions for the first three case studies

Case study	Solution number	Cost (\$M)	S_{ave}	I_m	I_r	MI_r
Two-loop	1	0.419	0.55	0.44	0.21	0.03
	2	0.423	0.66	0.03	0.35	0.04
	3	0.678	0.84	5.51	0.66	0.08
	4	4.4	0.93	12.73	0.9	0.11
NYT	1	38.64	0.72	0.02	0.42	0.07
	2	56.61	0.81	0.02	0.49	0.08
	3	89.28	0.86	0.41	0.52	0.09
	4	292.82	0.91	6.39	0.88	0.15
Hanoi	1	6.081	0.37	0.01	0.19	0.45
	2	6.365	0.48	0.07	0.21	0.49
	3	7.235	0.6	4.38	0.26	0.61
	4	10.97	0.74	19.62	0.35	0.83

In contrast, the available input power and internal resistance of the pipes have the biggest impact on the calculation of s_{ave} . It is clear from the results presented above that although s_{ave} focuses on a different aspect of network resilience compared with the other three network resilience measures investigated, s_{ave} is highly correlated with these measures and can be used as an indicator of the network resilience of a WDS.

9.5 Application results for the three-tank water transmission system

The solutions for the three-tank WTS (Wu et al., 2010a) are also generated using a multiobjective approach, in which the life cycle cost is minimized and s_{ave} is maximized. The life cycle cost is formulated as the sum of capital cost, pump refurbishment cost and operating cost. A design life of 100 years and a discount rate of 8% are used to calculate the pump refurbishment and operating costs. The life cycle cost evaluation process can be found in Wu et al. (2010a).

The Pareto-optimal front formed by 507 optimal solutions is presented in Figure 9.4. It should be noted that for this case study, the values of I_m , I_r and MI_r are always zero, regardless the configuration of the solution network, as water is delivered into tanks. Four typical solutions, which are marked using the unfilled square symbol and as solutions 1 to 4 in Figure 9.4, are selected for demonstration purposes. The network configurations of these four solutions are summarized in Table 9.3, and the flow distributions and s_{ave} values of these four solutions are summarized in Table 9.4.

Table 9.3 Network configurations of four typical solutions of the three-tank water transmission system case study

Solution number	Pipe diameter (mm)								Pump size (kW)	Pipe cost (\$M)
	Pipe 1	Pipe 2	Pipe 3	Pipe 4	Pipe 5	Pipe 6	Pipe 7	Pipe 8		
1	300	225	150	100	300	150	150	225	401	12.26
2	300	225	225	225	300	225	225	225	323	13.18
3	300	300	300	375	375	225	375	225	251	15.37
4	1,000	1,000	900	1,000	1,000	1,000	900	1,000	107	57.57

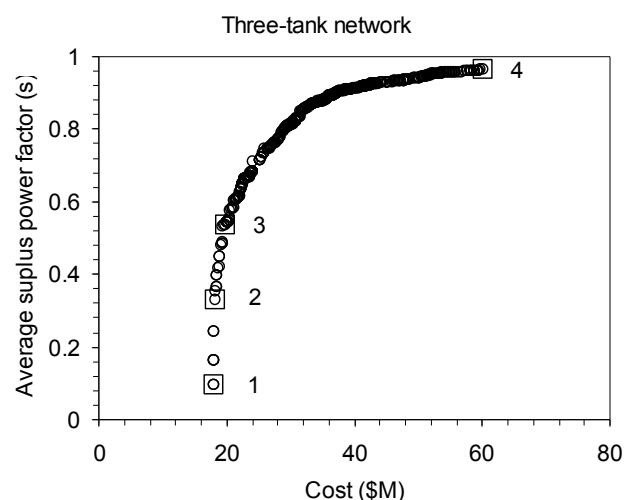


Figure 9.4 Pareto-optimal solutions of the three-tank water transmission network

It can be seen from Figure 9.4 that there are significant tradeoffs between life cycle cost and network resilience, as given by s_{ave} , for the three-tank WTS. Table 9.3 shows that as the pipe cost increases, the pump size decreases. This is because larger pipes result in smaller friction losses, which in turn reduces the power required to pump the required flow. The network resilience of this system is dependent on both pumping capacity and pipe sizes. As for this particular case study the pumps are sized according to the pipelines, pipe size dominates network resilience and thus the hydraulic reliability of the system. Solution 1 has the lowest pipe cost of \$12.26 million. Table 9.4 shows that the s_{ave} values of solution 1 are also the lowest, indicating a low level of network resilience. As the pipe sizes increase (moving from solution 1 to solution 4), the s_{ave} values increase accordingly, indicating an overall increase in network resilience level. However, the minimum s factors (s_{min}) of solutions 2 and 3 are still low, despite the increase in s_{ave} values. This is caused by the low s_{ave} values of pipe 1 of solution 2 and pipe 2 of solution 3. In contrast, solution 4

Table 9.4 Flow distribution and s factors of four typical solutions of the three-tank case study

Pipe number	Solution 1		Solution 2		Solution 3		Solution 4	
	Flow (L/s)	s factor	Flow (L/s)	s factor	Flow (L/s)	s factor	Flow (L/s)	s factor
1	129.66	0.0013	126.36	0.0168	121.04	0.0495	121.28	0.8720
2	60.34	0.0148	63.18	0.0096	81.98	0.0710	60.64	0.9521
3	48.72	0.0130	40.00	0.4388	40.49	0.7110	40.01	0.9810
4	11.61	0.0101	23.18	0.5243	41.49	0.7614	20.64	0.9885
5	40.00	0.7143	46.36	0.6726	40.55	0.8334	41.27	0.9849
6	28.39	0.0019	23.18	0.5243	0.94	0.9730	20.64	0.9885
7	40.94	0.0008	40.00	0.4388	40.00	0.8356	40.01	0.9810
8	69.33	0.0014	63.18	0.0096	39.06	0.0632	60.64	0.9521
s_{ave}	0.0947		0.3294		0.5373		0.9625	
s_{min}	0.0008		0.0096		0.0495		0.8720	

has a more evenly distributed surplus power, which is also represented by the significantly reduced difference between the average and minimum s factors. Compared to solutions 1 to 3, the average and minimum s factors of solution 4 are significantly higher. However, the life cycle cost of solution 4 is two times higher than that of solution 3 and the pipe cost of solution 4 is quadrupled compared to that of solution 1.

9.6 Conclusions

In this research, the suitability of using the surplus power factor (s) as a measure of the network resilience of WDSs has been assessed. Similar to the majority of existing network resilience measures, such as the minimum surplus head (I_m), the resilience index (I_r), and the modified resilience index (MI_r), the surplus power factor does not consider mechanical failures of WDSs, such as pipe breakage or the absence of alternative supply paths. In contrast, it is predominately used to quantify the excess capacity of a system in relation to a specified hydraulic failure condition. However, the surplus power factor has one significant advantage over existing network resilience measures. As the calculation of the surplus power factor does not require the value of the output pressure head of a network, it can be used to evaluate the network resilience of water transmission systems (WTSs); whereas most existing surplus power based WDS hydraulic reliability measures cannot be applied to such systems.

In this research, the utility of the average surplus power factor (s_{ave}) as a network resilience measure was first tested by comparing it with three existing measures [the minimum surplus head (I_m), resilience index (I_r), and modified resilience index (MI_r)] for three WDS case studies. Then, a three-tank transmission system was used to illustrate the application of the surplus power factor as a network resilience measure for a WTS. It was found that there exist significant tradeoffs between the cost and network resilience

represented by the surplus power factor and the surplus power factor is highly correlated with the three existing network resilience measures for all three case studies considered. In addition, use of the surplus power factor as a network resilience measure was demonstrated for a WTS. Consequently, the surplus power factor can potentially be used as a network resilience measure to incorporate hydraulic reliability considerations into the optimization of WDSs and particularly WTSs.

9.7 Acknowledgments

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Chapter 10

Multiobjective Optimization of Water Distribution System Design Accounting for Economic Cost, Greenhouse Gas Emissions and Hydraulic Reliability

Publication 6

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Wu, W. (Candidate)

Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.

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Signed: Date:

Abstract

The optimization of water distribution systems (WDSs) is a complex problem that usually has multiple hydraulic constraints and design objectives. As a result, optimization techniques, such as multiobjective genetic algorithms, have been used to optimize WDSs. Apart from the traditional objective of minimization of the economic cost of the system, maximization of network hydraulic reliability levels and minimization of environmental impact, such as total life cycle greenhouse gas (GHG) emissions are two additional major design objectives of WDSs. In previous research, these two objectives have been incorporated into bi-objective WDS optimization individually, together with the traditional economic objective of minimizing the total life cycle cost of the system. However, these two additional objectives of hydraulic reliability maximization and GHG emission minimization have not been considered at the same time. This research extends previous research by incorporating economic, reliability and environmental objectives simultaneously into the optimization of WDSs via a multiobjective approach. The interaction of these three objectives in a three dimensional search space and the impact of the inclusion of the objective of hydraulic reliability maximization on the tradeoffs between the economic and environmental objectives are investigated via a case study. It is found that the inclusion of the third objective of maximizing hydraulic reliability in multiobjective WDS optimization introduces more practical and feasible solutions with reasonable cost, reduced GHG emissions and significantly improved reliability levels. The outcomes of this research provide useful insights into the optimization problem in order to assist the final decision making process.

10.1 Introduction

The optimization of water distribution systems (WDSs) is a complex problem that usually has multiple hydraulic constraints and performance criteria, which often result in a large number of possible solutions. In the past, optimization techniques, such as genetic algorithms have been used to solve WDS optimization problems (Simpson et al., 1994). WDS optimization problems are further complicated in that multiple design objectives need to be considered. Apart from the traditional objective of minimization of the economic cost of the system, maximization of network reliability levels and minimization of environmental impact, such as greenhouse gas (GHG) emissions are two additional major design objectives of WDSs, which have been incorporated (separately) in previous research.

In some of the earliest work on the reliability of WDSs, Gessler and Walski (1985) used the excess pressure at the worst node in the system as a measure of benefit in a pipe network optimization problem to ensure sufficient water with acceptable pressure is delivered to demand nodes. Li et al. (1993) extended network reliability analysis to include a portion of hydraulic reliability – the capacity reliability. This is defined as the probability that the carrying capacity of a network meets the demand. Schneiter et al. (1996) applied the concept of capacity reliability to a WDS optimal rehabilitation problem.

Multiobjective optimization of WDSs accounting for network reliability was first investigated by Halhal et al. (1997), in which the network cost and the total benefit (including the improvement in the pressure deficiencies in the network) were maximized. Since then, minimizing the head deficit at demand nodes has been used as a hydraulic capacity reliability measure in a number of multiobjective WDS optimization studies that considered both cost and system reliability (Savic, 2002; Keedwell and Khu, 2004; Jourdan et al., 2005; Atiquzzaman et al., 2006). In 2000, Todini (2000) introduced a resilience index approach that was incorporated together with minimization of cost into

multiobjective WDS optimization via a heuristic approach. Based on the resilience index, Prasad and Park (2004) introduced a network resilience measure and applied it to multiobjective genetic algorithm optimization of WDSs. Around the same time, Tolson et al. (2004) used a genetic algorithm coupled with the First Order Reliability Method (FORM) to obtain optimal tradeoffs between cost and reliability of WDSs represented by the probability of failure. Kapelan et al. (2005) applied a multiobjective approach to maximize the robustness of a WDS, which was represented as the possibility that pressure heads at all network nodes are simultaneously equal to or above the minimum required pressure. More recently, Jayaram and Srinivasan (2008) modified the resilience index introduced by Todini (2000) and applied it to the optimal design and rehabilitation of WDSs via a multiobjective genetic algorithm approach.

The inclusion of objectives related to environmental factors in WDS optimization initially focused on the minimization of the energy consumption of the system. Ghimire and Barkdoll (2007) reported that seven percent of the world's energy was used to pump and treat water for urban water users in 2000 and this electricity consumption was expected to rise due to ever increasing population and demand. For most countries, electricity is currently generated from non-renewable sources, such as fossil fuels. Thus, WDSs involving pumping pose a burden on the environment through energy consumption. Many studies have been considered to minimize energy consumption/cost of WDSs. A review of earlier studies was carried out by Ormsbee and Lansey (1994). Other WDS operation energy minimization studies include those by Pezeshk and Helweg (1996), Nitivattananon et al. (1996), Ilich and Simonovic (1998), van Zyl et al. (2004) and Ulanicki et al. (2007).

Direct environmental impacts of WDSs were not considered in the literature until 2006, when Dandy et al. (2006) used a single-objective approach to minimize the material usage, embodied energy and GHG emissions associated with the manufacture of PVC pipes. Since then, the focus of WDS optimization has switched to the incorporation of GHG emissions associated

with energy consumption. Wu et al. (2008b) first introduced GHG emission minimization as one objective into the multiobjective optimal design of WDSs. Dandy et al. (2008) used a multiobjective approach to optimize the cost and embodied energy when two different pipe materials were considered. In another study, Herstein et al. (2009b) included an environmental index as one of the objectives of a multiobjective WDS optimization problem, which is a single parameter consisting of measures of resource consumption, environmental discharges (including GHG emissions) and environmental impacts. In a subsequent study, Wu et al. (2010b) explored the tradeoffs between the traditional objective of minimizing life cycle economic cost and the environmental objective of minimizing life cycle GHG emissions in WDS design. They also investigated the impact of discount rates on these tradeoffs. In a related study, Wu et al. (2010a) investigated the impact of carbon pricing on the single-objective and multiobjective optimization of WDSs accounting for GHG emissions.

As can be seen from previous research, economic cost, hydraulic reliability and environmental impact, especially in terms of GHG emissions are important design criteria for WDSs. In the past, these three criteria have only been considered in a pairwise fashion: either minimization of economic cost and maximization of network hydraulic reliability or minimization of economic cost and minimization of GHG emissions. The integration of these three objectives into the optimization of WDSs is the focus of the research presented here, which extends previous research on multiobjective optimization of WDSs accounting for economic cost and GHG emissions by introducing hydraulic reliability maximization as a third objective to form a three-objective optimization problem. The impact of the incorporation of the hydraulic reliability objective on the tradeoffs between the economic objective of minimizing cost and the environmental objective of minimizing GHG emissions and the interaction of the three objectives in a three dimensional space are investigated via a WDS case study from the literature. A multiobjective genetic algorithm called water system multiobjective genetic algorithm (WSMGA), which was developed by Wu et al. (2010b) based on the state-of-the-art multiobjective genetic algorithm NSGA-II (Deb et al.,

2000), is used in this study to search for the Pareto-optimal solutions based on these three objectives.

In the remainder of this paper, the formulation of the proposed three-objective optimization problem is introduced. Then, the case study and associated assumptions are presented. Thereafter, the optimization results for the tradeoffs among the economic, environmental and hydraulic reliability objectives are analyzed for the case study. Conclusions are presented at the end.

10.2 Multiobjective WDS optimization problem formulation

The WDS optimization problem presented in this paper is formulated as a multiobjective design problem, in which the best combination of the values for decision variables need to be determined in terms of certain objectives such that a number of constraints are satisfied. Thus, the WDS optimisation problem investigated in this paper can be expressed using the following equations:

$$\text{minimise/maximise} \quad OF_i = f(\vec{x}) \quad i = 1, 2, \dots, m \quad (10.1)$$

subject to

$$GF_j \geq 0 \quad j = 1, 2, \dots, p \quad (10.2)$$

$$HF_k = 0 \quad k = 1, 2, \dots, q \quad (10.3)$$

and

$$LB_t \leq x_t \leq UB_t \quad t = 1, 2, \dots, n \quad (10.4)$$

where OF = objective functions; \vec{x} = vector of decision variables; n = the number of decision variables; m = the number of objectives; GF = inequality constraint functions; p = the number of inequality constraints; HF = equality constraint functions; q = the number of equality constraints; LB_t and UB_t are the lower bound and upper bound of the t th decision variable, respectively.

In this paper, the decision variables of the WDS optimisation problem considered include pipe sizes, which often take discrete values, thus Eq. (10.4) can be expressed as:

$$x_t \in \{x_{t1}, x_{t2}, \dots, x_{tl}\} \quad (10.5)$$

where, $\{x_{t1}, x_{t2}, \dots, x_{tl}\}$ are the l discrete values of the t th decision variable.

The constraints of the WDS optimisation problems considered in this paper mainly include hydraulic constraints, available options of decision variables and case study specific constraints. Hydraulic constraints refer to the physical rules that a hydraulic system must obey, which include:

1. conservation of mass: The continuity of flow must be maintained at each node in the network;
2. conservation of energy: The total head loss around a loop must be zero and the total head loss along a path must equal the difference between the water elevations at the two end reservoirs.

The available options of decision variables include available diameters of pipes. The case study specific constraints include minimum allowable pressures at demand nodes.

In this study, three objectives for the design of WDSs are considered, which include: 1) minimization of the total life cycle cost of the system; 2) minimization of the total life cycle GHG emissions from the system; 3) maximization of the hydraulic reliability of the system. The evaluation of the three objective functions (separately) have been presented in previous studies

(Wu et al., 2010a; Wu et al., 2010b; Wu et al., 2011), but are summarized in the following section for the sake of completeness.

10.3 Objective function evaluation

10.3.1 Evaluation of total life cycle cost

The total life cycle cost of a WDS considered in this paper includes capital costs, operating costs and maintenance costs (Wu et al., 2010b). The capital cost consists of pump station cost, initial pump cost and pipe cost. Pump station cost and initial pump cost can be estimated based on the size of the pump, which is usually determined based on the network configuration and the peak-day demand (Wu et al., 2010b). Pipe cost is a function of pipe diameter and corresponding pipe length. Operating costs mainly result from the electricity consumption of system operation related to pumping during the design life of the system. In this study, a design life of 100 years is assumed for pipes, which is consistent with the suggestion by the Water Services Association of Australia (2002). Maintenance costs considered in this study are mainly due to the maintenance of pumps, which are assumed to be refurbished every 20 years or four times during the design life of the system (Wu et al., 2010b). The calculation of both operating cost and pump refurbishment cost require present value analysis. In this study, a discount rate of 8% is used, which has been used in previous related studies (Wu et al., 2010a; Wu et al., 2010b; Wu et al., 2012a; Wu et al., 2012b).

The annual electricity consumption (*AEC*) due to pumping can be calculated using the following equation:

$$AEC = \sum_{t=1}^T \frac{P(t)}{\eta(t)_{motor}} \times \Delta t = \sum_{t=1}^T \frac{1}{1000} \frac{\gamma \times Q(t) \times H(t)}{\eta(t)_{pump} \times \eta(t)_{motor}} \times \Delta t \quad (10.6)$$

where, t is the time step [e.g. the time step in an extended period simulation (EPS)]; $P(t)$ is the pump power (kW); γ is the specific weight of water (N/m^3); $Q(t)$ is the pump flow (m^3/s); $H(t)$ is the pump head (m); $\eta(t)_{pump}$ and $\eta(t)_{motor}$ are the pump efficiency and motor efficiency, respectively; T is the number of time steps; and Δt is the duration of each time step (hours). In this study, a pump efficiency of 85% and a motor efficiency of 95%, which were used in previous similar studies (Wu et al., 2010a; Wu et al., 2012b), have been assumed in the computation of the *AEC* for each pump. The annual operating cost can be calculated by multiplying the *AEC* (in kWh) by the average electricity tariff (in \$/kWh) of the corresponding year. In this paper, a base electricity tariff of \$0.14/kWh is used for the first year of the design period. From the second year of the design period and onwards, the electricity tariff is assumed to increase at 3% per annum. The annual demand is assumed to be constant throughout the design life. A detailed discussion on the assumed electricity tariffs can be found in Wu et al. (2012a).

10.3.2 Evaluation of total life cycle GHG emissions

In this study, the total life cycle GHG emissions of a WDS are due to energy consumption related to the fabrication and use stages of the life cycle of a WDS (Wu et al., 2010b). The GHG emissions related to the energy consumption of the fabrication stage of a WDS are referred to as capital emissions. Only emissions from pipe manufacture are considered here as they represent the largest proportion of the impact (Filion et al., 2004). In order to calculate the energy consumption during the fabrication stage of a WDS, embodied energy analysis (EEA) is first used to convert the mass of pipes to their equivalent embodied energy. In this study, an embodied energy factor for ductile iron cement-mortar lined (DICL) pipes of 40.2 MJ/kg is used. This value was estimated by Ambrose et al. (2002) based on a combination of published data and actual factory manufacturing data.

Once the embodied energy consumption of a WDS is determined, emission factor analysis (EFA) is used to convert energy in MJ into GHGs in kg of CO₂-e (carbon dioxide equivalent). In practice, emission factor values may vary across regions and with time, depending on the makeup of electricity energy sources (for example, thermal, nuclear, wind, hydroelectricity, etc.). In this study, a base average emission factor of 0.98 kg CO₂-e/kWh is used for the first year of the design period, which was the full-fuel-cycle emission factor value of South Australia in 2007 (The Department of Climate Change, 2008). Thereafter, the emission factor is assumed to decrease linearly to 70% of the 2007 level at the end of the design period of 100 years due to Government policy of encouraging a move to cleaner energy in the form of renewable energy sources. The base emission factor is used to calculate capital emissions. A detailed discussion of the assumed GHG emission factors can be found in Wu et al. (2012a).

GHG emissions due to system operation of pumping are assumed to account for the majority of the emissions from the use stage of a WDS. The annual operating emissions are taken as the *AEC* [defined in Eq. (10.1)] multiplied by the average emission factor of the corresponding year. The operating emissions due to pumping also occur over time within the design period, however, no discounting (that is a discount rate of zero percent) is applied to the calculation of pumping GHG emissions based on the recommendation of the Intergovernmental Panel on Climate Change (IPCC) (Fearnside, 2002).

10.3.3 Evaluation of hydraulic reliability

Difficulties arise when applying the hydraulic reliability measures currently used in literature to a WDS involving the delivery of water into storage facilities. This is because the calculation of these measures requires the difference between the required and minimum allowed pressure heads at the outlet of a system. In a system where water is delivered into tanks or reservoirs, this difference between pressures is always zero; thus, the values of the above reliability measures are always zero. In 2006, Vaabel et al. (2006)

introduced the concept of the surplus power factor (s), which can be used to measure the resilience of a network subject to failure conditions, and thus the hydraulic reliability of the network, on the basis of both pressure and flow. As the calculation of the surplus power factor does not require the value of the pressure head at the outlet of the system, it can be used to measure the resilience, and thus the hydraulic reliability of a WDS involving delivery into storage facilities (Wu et al., 2011). As a result, the minimum surplus power factor in a network is used as the hydraulic reliability measure in the three-objective WDS optimization formulation proposed in this study.

The surplus power factor (s) developed by Vaabel et al. (2006) can be calculated using the following equation:

$$s = 1 - \frac{a+1}{a} \left[1 - \frac{1}{a+1} \frac{Q_{in}^a}{Q_{max}^a} \right] \frac{Q_{in}}{Q_{max}} \quad (10.7)$$

where a is the flow exponent, Q_{in} is the flow in the pipe and Q_{max} is the flow that leads to the maximum value of output power, which can be calculated using the following equation:

$$Q_{max} = \left(\frac{H_{in}}{(a+1)c} \right)^{\frac{1}{a}} \quad (10.8)$$

where, c is the resistance coefficient of the pipe and H_{in} is the head at the inlet of the pipe. For a detailed derivation of the s factor, please refer to Vaabel et al. (2006).

The value of s characterizes the hydraulic reliability of a WDS (Vaabel et al., 2006). The range of the s factor is from zero to 1. When s is equal to zero, the hydraulic system works at its maximum capacity. Under this condition, any leakage can result in hydraulic failure of the system in terms of meeting the needs of end water users, such as delivering enough water with sufficient

pressure. As the value of the s factor increases, the resilience of the system to failure conditions increases, and so does the hydraulic reliability of the system. However, as long as the system delivers water to end users, the value of s cannot reach 1, as under such conditions the friction loss within the pipe will be equal to H_{in} and there will be no flow in the pipe. For a detailed discussion of the application of the s factor for estimating the hydraulic reliability of WDSs, refer to Wu et al. (2011).

10.4 Case study

10.4.1 Network description

A WDS investigated by Duan et al. (1990) has been adopted and modified in this study to determine the impact of the incorporation of the hydraulic reliability objective on the tradeoffs between the economic objective of minimizing cost and the environmental objective of minimizing GHG emissions, as well as the interaction of the three objectives in three dimensional space. In the original study by Duan et al. (1990) six reliability parameters were included in the single-objective design process as constraints. In contrast, in this study, these reliability constraints are replaced by the hydraulic reliability objective of maximizing the minimum surplus power factor in the network. This is possible because the surplus power factor can be used to measure the hydraulic reliability of a piping system delivering water into reservoirs or storage tanks, as explained previously.

The network configuration of the case study is shown in Figure 10.1. The network consists of one pump, one storage tank, 36 pipes and 16 demand nodes. The 24 hour extended period simulation (EPS) with defined demands for every six hours (i.e. 12am to 6am, 6am to 12pm, 12pm to 6pm and 6pm to 12am) used in the original study is also used in this study. In the first EPS time step, the pump needs to both supply the required demand and fill the tank

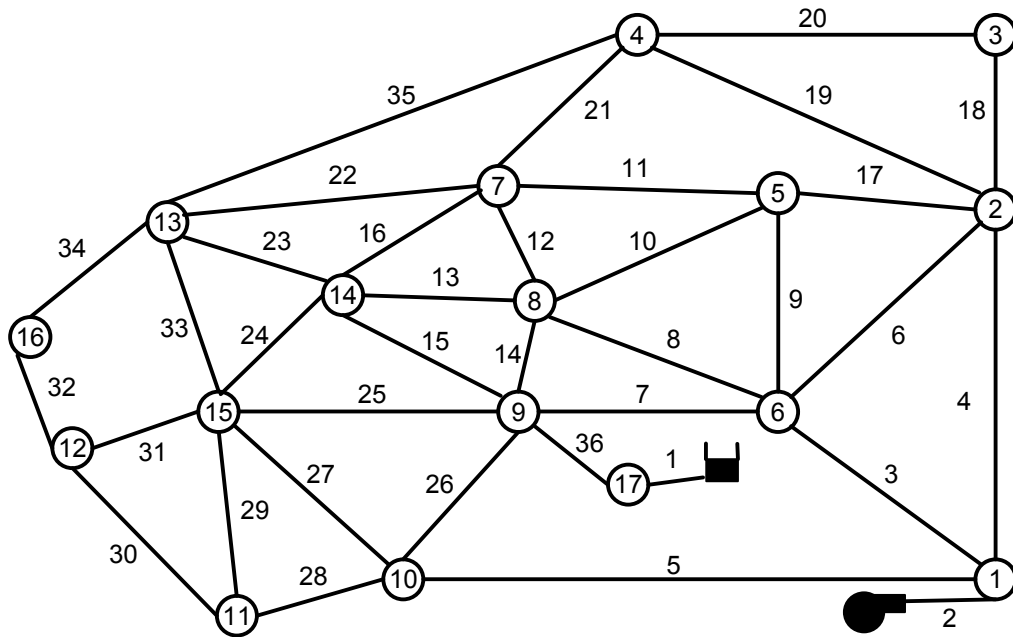


Figure 10.1 Network configuration [adapted from Duan et al. (1988)]

Table 10.1 Nodal information

Node	Demand for 12am to 6am (L/s)	Demand for 6am to 12pm (L/s)	Demand for 12pm to 6pm (L/s)	Demand for 6pm to 12am (L/s)	Elevation (m)
1	30.0	36.0	33.0	45.0	6.1
2	12.0	14.4	13.2	18.0	15.2
3	12.0	14.4	13.2	18.0	15.2
4	12.0	14.4	13.2	18.0	15.2
5	30.0	36.0	33.0	45.0	15.2
6	30.0	36.0	33.0	45.0	15.2
7	30.0	36.0	33.0	45.0	15.2
8	60.0	72.0	66.0	90.1	15.2
9	30.0	36.0	33.0	45.0	15.2
10	30.0	36.0	33.0	45.0	15.2
11	12.0	14.4	13.2	18.0	24.4
12	12.0	14.4	13.2	18.0	24.4
13	12.0	14.4	13.2	18.0	24.4
14	12.0	14.4	13.2	18.0	24.4
15	47.9	57.5	52.7	71.9	24.4
16	12.0	14.4	13.2	18.0	24.4
17	0	0	0	0	15.2

Table 10.2 Pipe lengths

Pipe No.	Length (m)	Pipe No.	Length (m)
1	15	19	2743
2	3	20	1829
3	3658	21	1829
4	3658*	22	1829
5	3658	23	1829
6	2743	24	1829
7	1829	25	1829
8	2438	26	1829
9	1829	27	1829
10	1829	28	1829
11	1829	29	1829
12	1829	30	1829
13	1829	31	1829
14	1829	32	1829
15	1829	33	1829
16	1829	34	3658
17	1829	35	3658
18	1829	36	15

*There is a discrepancy between the length of pipe 4 in the journal paper by Duan et al. (1990) (i.e. 1,200 feet) and that in the thesis by Duan (1988) (i.e. 12,000 feet). After examining the layout of the network, the authors chose the longer pipe length for pipe 4 presented in the thesis by Duan (1988), as it is more reasonable from a practical point of view.

completely; in the second EPS time step, demand is supplied by both the pump and tank; in the third EPS time step, the pump delivers the required demand and partially fills the tank that is drained during the previous time step; while in the last time step of the EPS, demand again is supplied by both the pump and the tank. For details of the EPS, please refer to Duan et al. (1990). The demands, node elevations and pipe lengths in US customary units in the original paper have been converted into SI units in this paper and are summarized in Tables 10.1 and 10.2, respectively. The minimum head requirements at the demand nodes are 28.1 m (or 40 psi). The sizes of the pumps are determined based on the network configurations evaluated in the optimization process (Wu et al., 2010b). Sixteen ductile iron cement mortar lined (DICL) pipes of different diameters are used as decision variable

Table 10.3 DICL pipe options

Option No	Diameter (mm)	Unit cost (\$/m)	Unit mass (kg/m)
1	100	228	17.7
2	150	307	30.0
3	225	433	50.9
4	300	568	74.1
5	375	813	99.1
6	450	1033	125.6
7	525	1252	153.6
8	600	1415	182.8
9	675	1658	213.1
10	700	1739	223.5
11	750	1900	244.5
12	800	1950	265.9
13	825	1976	276.8
14	900	2012	310.1
15	960	2040	337.3
16	1000	2142	355.7

options. The available sizes of the pipes, and their corresponding unit costs and unit masses are summarized in Table 10.3. The Darcy-Weisbach head loss formulation is used. In order to account for pipe aging, four roughness values (0.0015, 0.1, 0.5, 1.0 mm) are used, each of which is assumed to represent the average roughness of pipes of every consecutive 25 years of the design period.

10.4.2 Optimization parameters

In this study, the EPANET2 hydraulic model (Rossman, 2000) is used within the WSMGA optimization program for the purpose of constraint and objective function evaluation. For the case study, 100 separate multiobjective genetic algorithm optimization runs with different random seeds have been conducted to ensure (near) Pareto-optimal solutions are found. Consequently, the resulting optimal front for each case study is formed from the best solutions found in the 100 optimization runs. A population size of 500, a maximum number of generations of 3000, a probability of crossover of 0.9 and a

probability of mutation of 0.03 were used. The population size and generation number were selected based on the results of a number of test runs. The crossover probability was selected based on previous experience with optimization using genetic algorithms. The mutation probability was selected based on both test runs and the following rule of thumb: the probability of mutation is approximately equal to one over the length of the chromosome (the number of bits representing one individual). With the above genetic algorithm parameters, each multiobjective genetic algorithm run for the case study requires 14 CPU hours (2.66 GHz Intel Clovertown quad core processors), which result in a total of 1,400 CPU hours to conduct the 100 runs.

10.4.3 Optimization results and discussion

A total of 1,768 Pareto-optimal solutions were found in terms of the three objectives as part of the 100 optimization runs for the case study. In order to identify these solutions, they are ordered numerically from D1 (i.e. Design 1) to D1768 (i.e. Design 1768) based on their economic costs. In other words, Solution D1 is the lowest cost solution in terms of economic cost and Solution D1768 is the most expensive. The total life cycle cost of the solutions ranges from 44.2 million dollars for Solution D1 to 94.0 million dollars for Solution D1768; while the total GHG emissions of these solutions range from 309 kilo tonne (kt) for Solution D285 to 388 kt for Solution D1768; and the minimum s factor ranges from near zero for Solution D1 to 0.83 for Solution D1768. These Pareto-optimal solutions are plotted in Figure 10.2. The first plot in Figure 10.2 shows the three dimensional (3D) view of the Pareto-optimal front. Plots (b), (c) and (d) in Figure 10.2 show the optimal front from three different orientations: GHG emissions versus cost, minimum s factor versus cost and minimum s factor versus GHG emissions.

The Pareto-optimal front representing the tradeoffs among the total cost, GHG emissions and minimum s factor is close to a curve in the three-objective space, rather than a surface. This indicates that for the majority of the

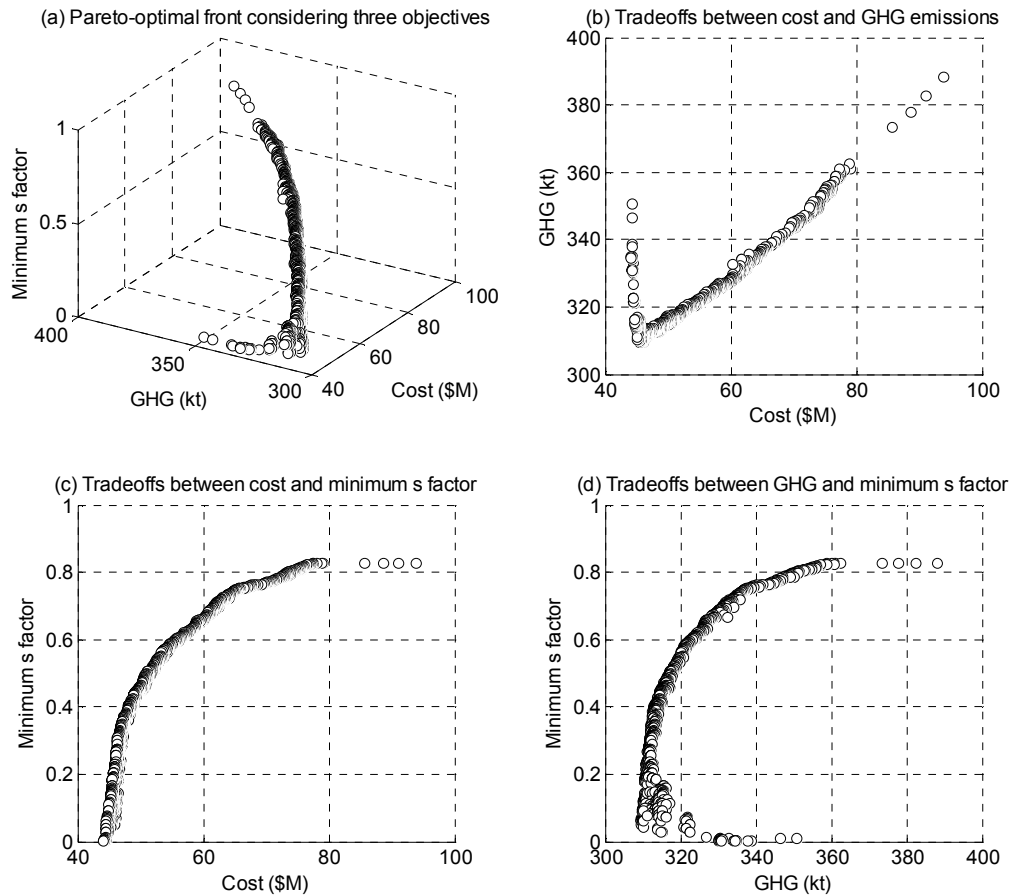


Figure 10.2 Different views of the Pareto-optimal front

objective space, the overall tradeoffs between the three objectives are dominated by the tradeoffs between two objectives only. This can be confirmed by the tradeoffs between each pair of the three objectives. Among the 1,768 Pareto-optimal solutions considering tradeoffs between all three objectives, there are only 44 solutions that are optimal if only the economic objective of minimizing cost and the environmental objective of minimizing GHG emissions are considered; and only 347 solutions are optimal if only the environmental objective of minimizing GHG emissions the hydraulic reliability objective of maximizing the minimum s factor are considered. In contrast, all of the 1,768 solutions are optimal when only the economic and hydraulic reliability objectives are considered. This demonstrates that the overall tradeoffs among the three objectives are dominated by the tradeoffs

between the economic and hydraulic reliability objectives in the majority of the objective space, as shown in Figure 10.2(c). The tradeoffs between the total life cycle cost and life cycle GHG emissions only exists in the low cost region, as shown in Figure 10.2(b); while in the higher cost region (i.e. economic cost higher than 46 million dollars), GHG emissions increase as the cost increases [Figure 10.2(b)], which results in the “V” shaped front from the economic-environmental-objective orientation of the Pareto-optimal front. The reason these high cost and high GHG solutions exist on the Pareto-optimal front is due to their high hydraulic reliability levels, represented by their high minimum s factor values.

In order to investigate the impact of the interaction of the three objectives on the physical configuration of the network, six representative solutions from different regions of the Pareto-optimal front are selected and analyzed. These solutions include the minimum cost solution (D1), which also has the lowest minimum s factor value, the minimum GHG emission solution (D285), the highest minimum s factor solution (D1768), which also has the highest cost and GHG emissions, and three other solutions (D33, D858 and D1265) representing different tradeoffs among the three objectives. The locations of these solutions in the objective space are shown in Figure 10.3. The breakdown of the life cycle cost, life cycle GHG emissions and minimum s factor values of these solutions are summarized in Tables 10.4 and 10.5, respectively. The network configurations of these solutions are summarized in Table 10.6.

In a traditional single-objective WDS optimization accounting for the minimization of the economic cost only, Solution D1 (see Figure 10.3) is the only optimal solution that will be found. Solution D1 has a total life cycle cost of 44.2 million dollars (Table 10.4). However, it will emit in total 335 kt of GHGs over the design life of the system and has a minimum s factor value of almost zero, as shown in Table 10.5. The fact that a near-zero s factor exists in the network is very undesirable, as it indicates that during at least one time step there is at least one pipe working at its maximum hydraulic capacity and

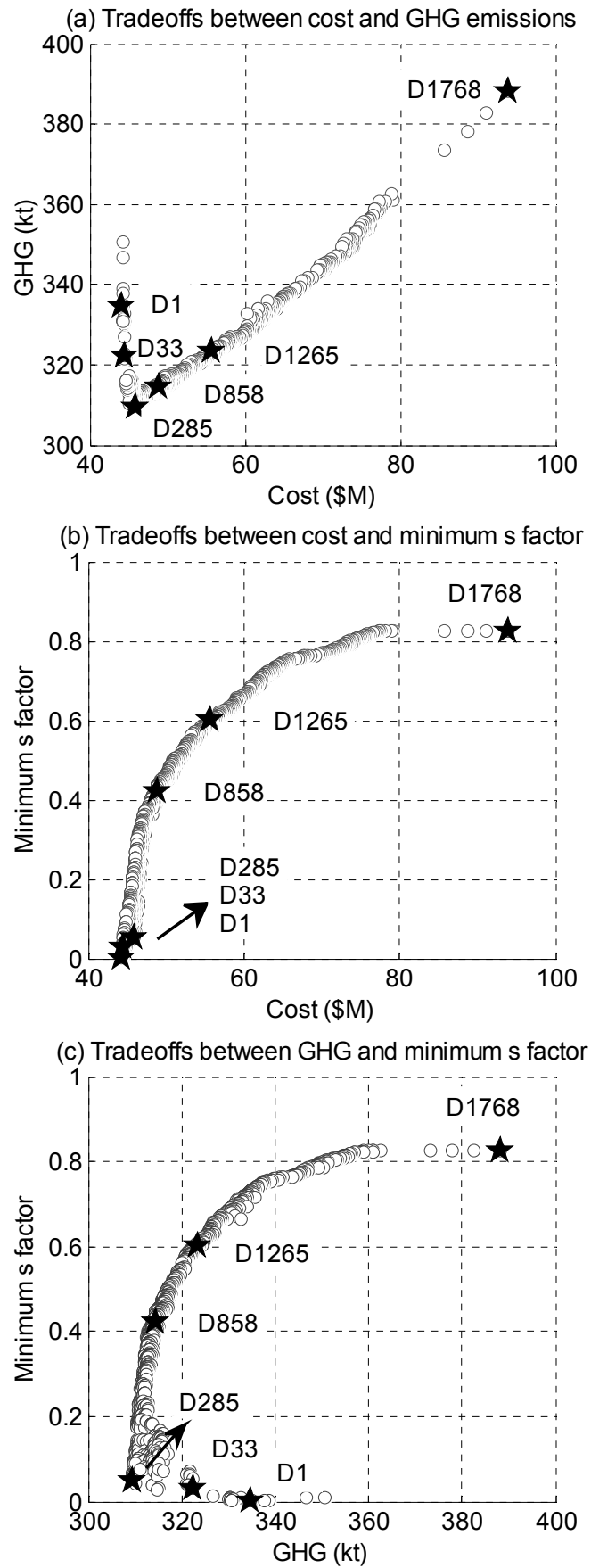


Figure 10.3 Locations of selected solutions in the objective space

Table 10.4 Breakdown of life cycle costs of selected solutions

Solution	Total cost (\$M)	Pump station cost (\$M)	Pipe cost (\$M)	Pump refurbishment cost (\$M)	Operating cost (\$M)
D1	44.2	2.2	31.9	0.5	9.6
D33	44.5	2.1	32.7	0.5	9.2
D285	45.9	1.9	34.9	0.4	8.7
D858	48.8	1.9	37.8	0.4	8.7
D1265	55.7	1.9	44.7	0.4	8.7
D1768	94.0	1.9	83.1	0.4	8.6

Table 10.5 Breakdown of life cycle GHG emissions and the minimum and maximum factors of selected solutions

Solution	Total GHG (kt)	Pipe GHG (kt)	Operating GHG (kt)	Minimum factor
D1	335	39	295	0.0002
D33	322	42	280	0.03
D285	309	47	262	0.05
D858	314	52	262	0.42
D1265	324	61	262	0.60
D1768	388	130	258	0.83

Table 10.6 Pipe diameters and objective function values of selected solutions

Pipe	Solutions					
	D1	D33	D285	D858	D1265	D1768
1	675	600	450	375	375	450
2	900	600	960	700	1000	675
3	100*	900	100*	300	450	1000
4	300	100*	300	375	450	1000
5	675	100*	1000	960	1000	1000
6	100	300	100	100	100	1000
7	300	600	225	225	100	800
8	100	100	100	100	100	225
9	300	300	100	100	300	375
10	100	100	225	300	300	750
11	100	300	100	100	100	675
12	100	100	225	300	375	300
13	100	100	100	100	100	225
14	300	300	450	525	600	700
15	300	300	225	225	300	525
16	225	100	100	100	150	700
17	100	100	100	100	225	1000
18	225	225	225	225	225	960
19	150	150	150	225	300	300
20	150	100	150	100	225	100
21	100	100	100	100	150	300
22	100	100	100	100	100	150
23	100	225	100	100	150	300
24	100	100	100	100	100	375
25	100	450	100	100	100	300
26	600	225	900	960	825	600
27	450	100	450	450	525	600
28	225	100	225	225	300	525
29	100	225	100	100	100	300
30	100	100	100	100	100	525
31	300	300	300	300	375	150
32	225	225	225	225	300	375
33	225	100	225	225	225	300
34	100	100	100	100	100	150
35	100	100	100	100	100	100
36	675	600	675	375	300	450
Total Cost (\$M)	44.2	44.5	45.9	48.8	55.7	94
Total GHG (kt)	335	322	309	314	324	388
Min. ϵ	0.0002	0.03	0.05	0.42	0.60	0.83

*Undesirable considering network reliability and real-world design practice.

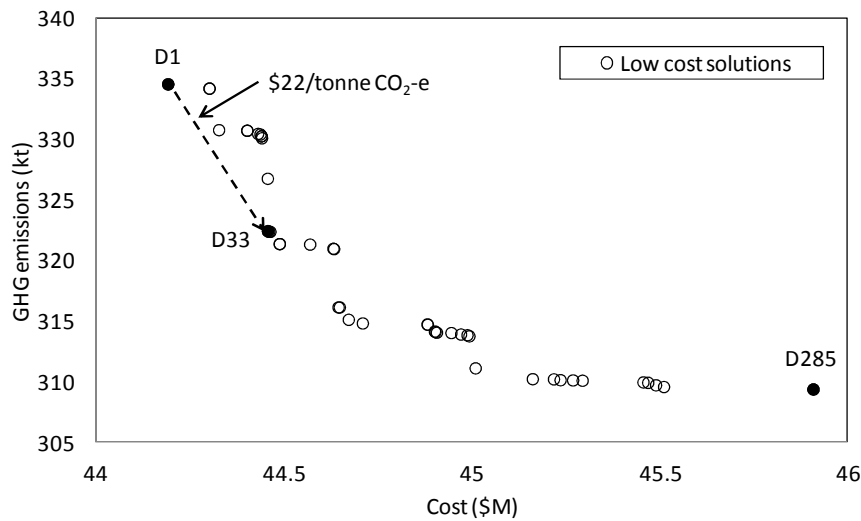


Figure 10.4 Carbon cost slope of selected low cost solutions

any leak could result in the failure of the system in terms of delivering sufficient water at required pressure to end water users. When GHG emission minimization is incorporated into the optimization of the system, another 43 solutions, apart from Solution D1, are Pareto-optimal. These 44 solutions represent the optimal tradeoffs between the minimization of the total life cycle cost and the minimization of the total life cycle GHG emissions [as presented in previous studies (Wu et al., 2010a; Wu et al., 2010b)] – an increase in the total cost and resultant reduction in the GHG emissions. These solutions provide decision makers with alternative design options, when considering the tradeoffs between the economic and environmental objective. Among these 44 solutions, Solution D285 generates the least GHG emissions of 309 kt, which is 13 kt less than those for Solution D1. However, Solution D285 is 1.7 million dollars more expensive compared with Solution D1. On the other hand, Solution D33 is the solution where the reduction in GHG emissions per unit of cost increase is maximized. The carbon cost of selecting Solution D33 instead of Solution D1 is \$22/tonne of CO₂-e based on the carbon cost slope concept introduced by Wu et al. (2010a), as shown in Figure 10.4. This carbon cost is lower than the Australian introductory carbon tax of 23 \$/tonne of

CO₂-e commencing from the 1st July 2012. In other words, Solution D33 represents the point where marginal returns are diminishing on the Pareto-optimal front obtained from optimizing the system accounting for the economic and environmental objectives at the currently proposed price of carbon. Consequently, Solution D33, which has a total cost of 44.5 million dollars and total GHG emissions of 322 kt (see Tables 10.4 and 10.5), is the best compromise solution when considering the optimal tradeoffs between the economic and environmental objectives. Both Solution D33 ($\alpha=0.03$) and Solution D285 ($\alpha=0.05$) have slightly improved hydraulic reliability levels compared with Solution D1 (see Table 10.5). However, the configurations of these three networks are not desirable from a practical point of view, as all of these networks have the minimum diameter (i.e. 100 mm) selected for at least one of the major pipes (i.e. pipes 3, 4 and 5, which are 3,658 m long) of the system (see Table 10.6). This is mainly because the economic objective of minimizing cost drives the search into low cost regions in the search space by trying to convert a looped network into a treed network, which is more cost effective.

When the third hydraulic reliability objective is incorporated into the design optimization, together with the economic and environmental objectives, another 1,724 solutions with higher hydraulic reliability levels are introduced to the Pareto-optimal front, which results in the “V” shaped view shown in Figures 10.2(b) and 10.3(a) as mentioned previously. These solutions generally have larger pipe diameters compared to the 44 optimal solutions considering the tradeoffs between the economic and environmental objectives, which results in both higher cost and GHG emissions. These solutions include the highest minimum α factor solution D1768, whose minimum α factor is 0.83 (see Table 10.5). This hydraulic reliability level is significantly higher than that of the solutions in the low cost regions (e.g. Solutions D1, D33 and D285). However, the cost of Solution D1768 is more than double that of the solutions in the low cost region and also generates extremely high GHG emissions, particularly due to the large capital GHG emissions contributed by the pipes (i.e. 388 kt in Table 10.5). Both the high cost and high GHG

emissions of Solution D1768 make it an undesirable design to implement in practice.

Among these high hydraulic reliability solutions, networks representing reasonable tradeoffs between reliability and economic cost, and reliability and GHG emissions exist. For example, Solution D858 is 4.6 million dollars (i.e. 10%) more expensive than solution D1; however, it generates 21 kt (i.e. 6.3%) less GHG emissions and significantly improves the hydraulic reliability of the system by raising the minimum s factor value in the system from near zero to 0.42 (see Table 10.5). Similarly, solution D1265 is 11.5 million dollars (i.e. 26%) more expensive than solution D1 (see Table 10.4); but reduces GHG emissions by 11 kt (i.e. 3.3%) and increases the minimum s factor value in the network to 0.60 (see Table 10.5). More importantly, the network configurations of both Solution D858 and Solution D1265 are more desirable from a practical point of view, with reasonable diameters selected for the major pipes (i.e. pipes 1, 2, 3, 4, 5 and 36), as can be seen from Table 10.6. This is an important finding, as it suggests that by including the hydraulic reliability, the optimization can lead to network solutions that are not only more reliable, but also more practically feasible and with reasonable cost and reduced GHG emissions.

In order to gain insight into the impact of the inclusion of the hydraulic reliability objective of maximizing the minimum s factor on multiobjective WDS design optimization, the conditions under which the minimum s factor value occurs in the selected networks are summarized in Table 10.7. As can be seen, for the majority of cases, the minimum s factor occurs at one of the major pipes in the network (e.g. pipes 3, 4 and 5), and this is almost certain if the major pipe also has the minimum diameter of 100 mm. This is due to the high head loss in these pipes. As shown in Table 10.7, the minimum s factor value often occurs in the pipe where the maximum head loss occurs. This indicates that by including the maximization of the minimum s factor in the network as a third objective in the optimization, the optimization algorithm explores higher reliability regions by increasing the diameters of the pipes

Table 10.7 The locations and conditions at which the minimum surplus power factor occurs in the selected network solutions

Solutions	Pipe	Time step	Diameter (mm)	Inlet head (m)	Outlet head (m)	Flow (L/s)	Head loss (m)	Note
D1	3	1	100	84.5	57	4.8	27.5	Maximum head loss.
D33	5	1	100	75.2	56.8	3.9	18.4	Maximum head loss.
D285	3	4	100	61	48.2	3.3	12.8	Maximum head loss.
D858	17	1	100	62.7	59.2	2.4	3.46	Maximum head loss.
D1265	3	4	450	59.6	58.1	59.8	1.48	Second highest head loss.
D1768	4	1	1000	61.7	61.4	208.9	0.28	Maximum head loss.

where high head losses occur, which in a sense produces a counter effect to the motivation of searching for low cost regions driven by the economic objective of minimizing cost. This effect increases pipe costs and GHG emissions, but reduces operating costs and emissions in the low cost region. However, the operating costs and emissions cannot be reduced to zero due to the static head of the system against which the pumps need to work. Therefore, after the balance between the increase in the capital component of the cost or GHG emission and the operating component of the cost or emissions is reached, a further increase in the minimum ϵ factor value in the network will result in significant increases in both economic cost and GHG emissions.

In contrast, as can be seen in Table 10.7, the flow within the pipe and the pressure head at the outlet of the pipe can vary and are independent from the value of the ϵ factor. This is because the ϵ factor measures the hydraulic reliability of a WDS on the basis of both pressure and flow simultaneously, rather than separately (Vaabel et al., 2006). Therefore, there is no obvious direct relationship between the ϵ factor and the output pressure head or between the ϵ factor and the flow independently. In addition, all of the minimum ϵ factor values occurred in the first or the last time step of the EPS. This is because in these two time steps, the system is under more hydraulic pressure - in time step one, demand is only delivered by the pump and the pump needs to fill the tank to capacity at the same time; while demand is highest in time step four.

10.5 Conclusions

The study presented in this paper extends previous research on multiobjective WDS optimization accounting for economic cost and GHG emissions by incorporating the third hydraulic reliability objective of maximizing the minimum surplus power factor (ϵ) into the optimization process. A case study water distribution system (WDS) with one pump, one tank, 36 pipes and 16

demand nodes from the literature has been modified and used as a case study to explore the interaction of the objectives in a three dimensional space and to investigate the impact of the inclusion of the third hydraulic reliability objective on the tradeoffs between the economic and environmental objectives.

The optimization results show that the tradeoffs between the economic, environmental and reliability objectives manifest themselves as a three dimensional curve, and are largely dominated by the tradeoffs between the economic objective of minimizing life cycle cost and the hydraulic reliability objective. Consequently, the inclusion of the third hydraulic reliability objective introduced a large number of solutions into the Pareto-optimal front in addition to the optimal solutions expressing the tradeoffs between the economic objective of minimizing life cycle cost and the environmental objective of minimizing life cycle GHG emissions. These solutions often have higher economic cost and GHG emissions compared with the optimal solutions considering tradeoffs between the economic and environmental objectives. However, the reliability levels of these solutions are improved significantly compared to the optimal solutions considering the economic and environmental objectives only. In addition, it has been found that the optimal solutions considering the tradeoffs between the cost and GHG emission only are often undesirable from a practical point of view, as they often include the minimum diameter for one of the major pipes of the network in order to reduce the economic cost by trying to convert a looped network into a treed network. However, the inclusion of the third hydraulic reliability objective creates a counter effect to this drive created by the economic objective and leads to solutions that are more practically desirable and with reasonable cost and reduced GHG emissions.

In conclusion, the incorporation of the third hydraulic reliability objective of maximizing the minimum λ factor of the system into multiobjective WDS optimization accounting for economic cost and GHG emission minimization presents valuable additional information for the final decision making process by providing more alternative solutions. These solutions are not only more

reliable, but also reasonably priced and often with reduced GHG emissions. More importantly, many alternative solutions resulting from the inclusion of the third hydraulic reliability objective are more feasible for practical implementation.

10.6 Acknowledgements

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Chapter 11

Conclusions

Multiobjective optimization is becoming an increasingly important approach for both the design and operation of water distribution systems (WDSs). Given the multiobjective nature of these problems, multiobjective optimization is expected to provide decision makers with increased insight into the tradeoffs between competing objectives and alternative solutions of WDSs which may benefit the water industry, society and environment. Due to the advances in computing technology and the development of fast multiobjective sorting algorithms, research activities in the application of multiobjective algorithms to WDS design and operation have increased significantly in the past decade. More environmental related issues, such as energy conservation, have been incorporated into the optimization of WDSs. However, the leading environmental concern – Greenhouse gas (GHG) emissions – has not been addressed directly in the field of WDS optimization. Consequently, in the research presented in this thesis, GHG emission minimization has been incorporated directly into the optimal design of WDSs via a multiobjective approach, together with the economic objective of minimizing cost and the reliability objective of maximizing hydraulic reliability of a network.

11.1 Research contributions

The overall contribution of this research is the incorporation of GHG emission minimization into the optimal design of WDSs via a multiobjective approach, together with the traditional economic and reliability objectives. Ultimately, it is hoped that this will lead to the consideration of environmental objectives and the adoption of a multiobjective framework for the design of WDSs in the real world. The details of specific contributions of this research are as follows:

1. The first contribution of this research is the development of a framework for evaluating the life cycle GHG emissions of WDSs and to incorporate them into the optimization of WDS design via a multiobjective approach. This is the first time that GHG emissions have been directly considered in WDS optimization as a design objective via a multiobjective approach. It is hoped that this research will open the gate to a new paradigm for the design and operation of WDSs.
2. The second contribution of this research is that it provides insight into the tradeoffs between the economic objective of minimizing life cycle cost and the environmental objective of minimizing life cycle GHG emissions of WDS designs. By using multiobjective optimization, a set of optimal solutions, rather than one optimal solution, is obtained. Each of these optimal solutions is unique in that each of them provides different tradeoffs or preference between the two objectives. For example, in some instances, a small additional economic investment at the beginning of the project can result in a reduction in both economic cost and GHG emissions from a WDS in the long run. These tradeoffs can be represented using the carbon cost slope (see Figure 5.5) developed in this research, which is expressed as the increase in economic cost in terms of every unit reduction in GHG emissions. The development of this carbon slope concept is an important contribution of this research and it can be used to compare the effectiveness of reducing GHG emissions from selecting different Pareto-optimal solutions. Insights such as these

improve designers' understanding of the design search space and the alternative solutions provide decision makers with an avenue for influencing Government policy in relation to the reduction of GHG emissions into practice.

3. This research investigates the impact of a potential emissions trading scheme, where carbon related emissions are priced, on the way GHG emissions are incorporated into the optimization of WDSs. Once a monetary carbon price is determined by either evaluation methods or a carbon market, the environmental objective function value, which is generally expressed in tonnes of GHG emissions, can be converted into dollars, which enables a single-objective approach to be used. This raises the question of whether the introduction of carbon pricing under an emissions trading scheme will make the use of a multiobjective approach for WDS optimization obsolete or whether such an approach can provide additional insight that is useful in a decision-making context. This question is explored by comparing single-objective and multiobjective approaches for WDS optimization accounting for GHG emissions. The comparison results clearly demonstrate that even though the single-objective approach is easier to implement and can lead to a simpler decision-making process, the multiobjective approach is far superior than the single-objective approach in that: 1) it provides decision makers more insight into the WDS optimization problem by showing the tradeoffs between competing objectives explicitly; 2) a carbon cost mapping of the objective space can be obtained, which can be used to determine the single-objective optimal solution for any given carbon price; and 3) the multiobjective approach provides decision makers with a clear indication of the effectiveness of a specific carbon price in reducing GHG emissions relative to other carbon prices.

4. The sensitivity of the tradeoffs between the economic and environmental objectives of WDS optimization to discount rate, electricity tariffs and emission factors used in the objective function evaluation process is also investigated in this research. The sensitivity analysis results show that the

discount rate and electricity tariffs have little impact on the life cycle GHG emissions of WDSs. However, a lower discount rate and higher electricity tariffs into the future can remove some higher GHG emission solutions from the Pareto-optimal front obtained using multiobjective optimization, which potentially leads to a WDS design with lower GHG emissions. The emission factors have a significant impact on the life cycle GHG emissions of WDSs. As a result, switching from combustion of fossil fuels to renewable energy sources, such as solar, wind or hydroelectric energy, is an effective method of reducing GHG emission from WDSs. Based on the results of this research, decision makers are able to gain access to insight in relation to how Government policies could help to mitigate global warming by reducing GHG emissions from the water industry.

5. Another major contribution of this research is the development of a pump power estimation method which enables the incorporation of variable speed pumps (VSPs) in the optimization of the design of WDSs. VSPs have been used in the optimization of the operation of existing WDSs in the literature. However, due to the dynamic natures of VSPs, direct consideration of VSPs in the optimization of the design of WDSs remains a challenge and consequently fixed speed pumps (FSPs) are often used. This research addresses this problem by introducing an optimization based pump power estimation method, which can be used to quickly and repeatedly estimate the pumping energy consumption of a large number of network configurations within an optimization process. This research demonstrates that switching from FSPs to VSPs for new WDSs is another effective way of reducing GHG emissions from WDSs.
6. Hydraulic reliability is an important aspect for the design of WDSs. Therefore, a number of studies have been dedicated to incorporating hydraulic reliability considerations into the optimization of WDSs. However, the hydraulic reliability measures commonly used cannot be used for WDSs involving pumping water into reservoirs or storage tanks, which are often the primary cause of GHG emissions. Consequently, one

part of this research has involved finding a suitable hydraulic reliability measure for such WDSs and assessing the applicability of this measure as an indicator of the hydraulic reliability of WDSs. The results of this research enable the investigation of tradeoffs between economic and hydraulic reliability objectives for WDSs involving pumping water into storage facilities.

7. In this research, the environmental objective of minimizing the life cycle GHG emissions is incorporated into the optimization of WDSs together with the economic objective of minimizing life cycle cost and the hydraulic reliability objective of maximizing the minimum surplus power factor of a network via a multiobjective approach for the first time. The tradeoffs among the three competing objectives manifest themselves as a three dimensional curve, and are largely dominated by the tradeoffs between the economic and hydraulic reliability objectives. Consequently, the inclusion of the third hydraulic reliability objective introduced a large number of solutions into the Pareto-optimal front in addition to the optimal solutions expressing the tradeoffs between the economic and environmental objectives. These alternative solutions are generally more expensive, but with significantly improved hydraulic reliability levels. More importantly, it has been found that the inclusion of the hydraulic reliability objective of maximizing surplus power factor can direct the optimization algorithm to search for solution networks that are more feasible to implement in practice, but still have reasonable cost and reduced GHG emissions.
8. A significant amount of this research has been dedicated to the development of a multiobjective genetic algorithm called the water system multiobjective genetic algorithm (WSMGA), which is used throughout the course of this research. WSMGA is developed based on the state-of-art multiobjective genetic algorithm NSGA-II (non-dominated sorting genetic algorithm II). The original binary coding scheme in NSGA-II has been replaced by an integer coding scheme, which caters for the discrete decision variables generally encountered in

WDS optimization problems An archive strategy used in the Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler et al., 2002) is also incorporated into the development of WSMGA in order to improve its performance. In addition, an extra function has been developed for WSMGA to implement the optimization based pump power estimation method proposed in Chapter 7.

11.2 Publications

Apart from the six journal articles which form the main body of this thesis, nine conference papers have also resulted from this research. A list of all of the publications arising from this research is presented below.

Journal articles:

1. Wu, W., Simpson, A. R., and Maier, H. R. (2010). "Accounting for Greenhouse Gas Emissions in Multiobjective Genetic Algorithm Optimization of Water Distribution Systems." *Journal of Water Resources Planning and Management*, 136(2), 146-155.
2. Wu, W., Maier, H. R., and Simpson, A. R. (2010). "Single-Objective versus Multi-Objective Optimization of Water Distribution Systems Accounting for Greenhouse Gas Emissions by Carbon Pricing." *Journal of Water Resources Planning and Management*, 136(5), 555-565.
3. Wu, W., Simpson, A. R., and Maier, H. R. (2012) "Incorporation of Variable-speed Pumping in Multiobjective Genetic Algorithm Optimization of the Design of Water Transmission Systems." *Journal of Water Resources Planning and Management*, (in press).
4. Wu, W., Maier, H. R. and Simpson, A. R. (2012). "Sensitivity of Optimal Tradeoffs between Cost and Greenhouse Gas Emissions for Water

Distribution Systems to Electricity Tariff and Generation.” *Journal of Water Resources Planning and Management*. 138(2), 182-186.

5. Wu, W., Maier, H. R. and Simpson, A. R. (2011) “Surplus Power Factor as a Resilience Measure for Assessing Hydraulic Reliability in Water Transmission System Optimization.” *Journal of Water Resources Planning and Management*. 137(6), 542-546.
6. Wu, W., Maier, H. R. and Simpson, A. R. (2012). “Multiobjective Optimization of Water Distribution System Design Accounting for Economic Cost, Greenhouse Gas Emissions and Hydraulic Reliability.” *Water Resources Research*. (submitted).

Conference articles:

1. Wu, W., Maier, H. R., and Simpson, A. R. (2008). "Genetic Algorithm Optimization of Water Distribution Systems Accounting for Greenhouse Gas Emissions." 9th National Conference on Hydraulics in Water Engineering, Engineers Australia, Darwin Convention Centre, Australia.
2. Wu, W., Simpson, A. R., and Maier, H. R. (2008). "Multi-objective Genetic Algorithm Optimization of Water Distribution Systems Accounting for Sustainability." Water Down Under 2008: Incorporating 31st Hydrology and Water Resources Symposium and the 4th International Conference on Water Resources and Environment Research (ICWRER), Adelaide, Australia.
3. Wu, W., Simpson, A. R., and Maier, H. R. (2008). "Water Distribution System Optimization Accounting for a Range of Future Possible Carbon Prices." 10th Annual Symposium on Water Distribution Systems Analysis, American Society of Civil Engineers, Kruger National Park, South Africa.
4. Wu, W., Maier, H. R., and Simpson, A. R. (2009). "Multi-objective Water Distribution System Optimization Accounting for Carbon

Emissions under Different Electricity Tariffs." Ozwater '09, Melbourne, Australia.

5. Wu, W., Simpson, A. R., and Maier, H. R. (2009). "Accounting for Carbon: Selecting the Right Discount Rate for Multi-objective Optimization of Water Distribution System." SA Branch Regional Conference & Operators Forum, Australian Water Association, Adelaide, Australia.
6. Wu, W., Simpson, A. R., and Maier, H. R. (2009). "Trade-off Analysis between Cost and Reliability of Water Distribution Systems Using Genetic Algorithms." Computing and Control in the Water Industry 2009 'Integrating Water Systems', London, U.K.
7. Wu, W., Simpson, A. R., and Maier, H. R. (2010). "Reducing Carbon Footprint from Water Distribution Systems by Using a Lower Discount Rate." Practical Responses to Climate Change National Conference 2010, Engineers Australia, Melbourne, Australia.
8. Wu, W., Simpson, A. R., and Maier, H. R. (2010). "Accounting for Carbon: Selecting the Appropriate Discount Rate for Multi-objective Optimization of Water Distribution Systems." Ozwater'10, Australia Water Association, Brisbane, Australia.
9. Wu, W., Simpson, A. R., and Maier, H. R. (2011). "Reducing Greenhouse Gas Emissions from Water Distribution Systems using Multi-objective Optimization and Variable Speed Pumping." OZWater'11, Australian Water Association, Adelaide.

The third conference paper listed above won the Second Best Paper Award at the 10th International Water Distribution Systems Analysis (WDSA) Conference, American Society of Civil Engineers, in South Africa, 17-20 August, 2008.

11.3 Research limitations

The limitations of this research are discussed below:

1. The estimates of life cycle cost and GHG emissions in this research are dependent on the data available. Due to limited data, capital emissions from the manufacture of network components other than pipes, such as pumps, valves and storage tanks, could not be included. In addition, the emission factors used in this research are for South Australia only. However, many network components are manufactured in developing countries, where the emission factors are higher than in South Australia. As a result, the proportion of capital GHG emissions in the life cycle GHG emissions may be higher than those indicated in this research. Despite the limitation of the available data, the methodology presented in this research can be applied to WDS optimization in any region or country where the required data are available.
2. Estimation of operating energy consumption of WDSs due to pumping is an important step in the evaluation of the economic and environmental objective functions of the multiobjective WDS optimization framework proposed in this research. The pumping energy consumption of a WDS is best estimated using extended period simulation (EPS). However, it is very difficult to incorporate EPS over a long design period (e.g. 100 years) with specific operational rules for each of the tens of thousands of network configurations that need to be evaluated in a design optimization process. As a result, in Chapter 6, a 48-hour EPS and generic rules are used for pumping energy estimation. However, EPS with generic operational rules can introduce bias and uncertainties into the optimization process, as the generic rules may suit some network configurations better than others. Consequently, whether or not to use EPS and/or how to incorporate EPS into the design optimization of WDSs with a long design life (e.g. 100 years) remains a question.

3. The pump power estimation method proposed in Chapter 7 requires repeated calculation of flows and heads in one time step in an EPS, which cannot be done in the EPANET2 hydraulic solver used in this research. As a result, whenever the pump power estimation method is used in this research, a simplified EPS with a number of steady states, each representing a time step, is used. Consequently, implementing the pump power estimation method proposed in this research with real EPS including interactions between pumps and tanks remains an area of further research.
4. Finding global best Pareto-optimal solutions has always been the focus in multiobjective optimization. However, in practice, not all optimal solutions can be implemented with the desired precision for various reasons. One major reason for this is that the globally optimal solution is sensitive to variable perturbations in its vicinity (Deb and Gupta, 2005). Therefore, robustness is an important consideration in multiobjective optimization. The sensitivity study conducted in Chapter 8 is the first step towards addressing the robustness issue in the multiobjective optimization of WDSs. However, this issue needs to be explored further in future research.
5. The majority of the case studies used in this research are hypothetical networks, and are relatively small in scale compared to real world WDSs. It is anticipated that the methodologies developed in this research based on these hypothetical case studies can be easily applied to real world case studies. However, the applicability of the framework to real world systems remains untested.
6. The WSMGA software developed in this research is a typical research program and users need to know the C programming language in which it is written in order to use it. This limits the potential users of the program, and a user interface which enables users to input data and automatically generate outputs (e.g. Pareto-optimal fronts) would significantly increase the usefulness of the software.

11.4 Recommendations for future work

A number of the limitations of the current research presented in the previous section also represent opportunities for future research, including:

1. Multiobjective WDS optimization accounting for GHG emissions relies on a large amount of data, such as embodied energy of network work components and emission factors, for GHG emission estimation. Data collection and estimation for evaluating GHG emissions has been done for some regions and in some disciplines (Treloar, 1994; The Department of Climate Change, 2008). Such work should continue to assist GHG emission evaluation in every field, including WDS optimization.
2. There is no doubt that the inclusion of accurate EPS with realistic operational rules will improve the estimation of pumping energy consumption of WDSs. Future work should consider the development of a dynamic EPS that changes over time based on future demand. A methodology is also needed to take into account the uncertainties and bias that can be introduced by the inclusion of EPS in the optimal design of WDSs, particularly for systems with a long design life, such as 100 years.
3. The pump power estimation method proposed in this research can be used to incorporate both FSPs and VSPs into the design optimization of WDSs. However, as mentioned in the previous section, the method cannot be implemented with EPS when EPANET2 is used as the hydraulic solver. Future research should consider the use of an alternative hydraulic solver, which can repeatedly calculate the flows and heads of the network at each time step of an EPS. This would enable the inclusion of VSPs together with EPS in the optimal design of WDSs using optimization.
4. There is a need to incorporate robustness considerations into the multiobjective optimization of WDSs. This would enable the sensitivity of the optimal solutions to the perturbation of variables and parameters to

be taken into account. This will improve the precision of the implementation of the design in the real world and potentially eliminate or reduce the number of costly redesigns.

5. Future research should consider the application of the multiobjective WDS optimization framework developed in this research to real world WDSs.
6. The WSMGA is developed purely for research purposes and is not very user friendly. Further work should consider improving the program by including a user-friendly interface. In addition, during the course of this research, a number new algorithms claiming to perform better than NSGA-II, such as the non-dominated ranking genetic algorithms or NPGA (Jadaan et al., 2008), have been developed for multiobjective optimization. The performance of the program can be improved by incorporating the key features of these newly introduced algorithms.

Other opportunities for further research include:

7. This research focuses on the optimal design of new WDSs accounting for economic cost, GHG emissions and hydraulic reliability. The framework developed in this research can easily be revised to account for economic cost, GHG emissions and the hydraulic reliability of existing WDSs. Thus, optimizing operational strategies of existing WDSs accounting for multiple objectives, including GHG emission minimization, remains a research opportunity.
8. The parameter setting of a genetic algorithm (GA) has a significant impact on its performance. When a GA is calibrated correctly, its performance will be maximized for a given problem formulation (Gibbs, 2008). The WSMGA parameters used in this research are determined based on a number of trial studies and the author's experience with GAs. However, a systematic study is required to develop a methodology to determine the most suitable multiobjective GA or WSMGA parameter

settings for a given WDS optimization problem. This will improve the confidence in the Pareto-optimal solutions obtained using the algorithm.

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Appendix A

Sample Code

Appendix A1: Sample *evaluatepop* function code in C

Appendix A2: Sample WSMGA input file “*input.in*”

Appendix A3: Sample UNIX system script “*job*”

Appendix A4: Sample UNIX system script “*runjobs*”

Appendix A1: Sample code for the *evaluatepop* function in C

The sample code for the *evaluationpop* function is contained in the compact disc attached to this thesis.

Appendix A2: Sample WSMGA input file “*input.in*”

```

3000 // number of generations
500 // number of population
2 // number of objective functions
3 // number of constraints
1.0 // possibility of crossover
0.1 // possibility of mutation
8 // number of integer DVs*
1 // the input options are the same
16 // number of options for each DV
100 228 17.70 0 0 // 1st options for DV: dia., cost, mass
150 307 30.02 0 0 // 2nd options for DV
225 433 50.91 0 0 // 3rd options for DV
300 568 74.07 0 0 // 4th options for DV
375 813 99.07 0 0 // 5th options for DV
450 1033 125.64 0 0 // 6th options for DV
525 1252 153.60 0 0 // 7th options for DV
600 1415 182.79 0 0 // 8th options for DV
675 1658 213.12 0 0 // 9th options for DV
700 1739 223.46 0 0 // 10th options for DV
750 1900 244.49 0 0 // 11th options for DV
800 1950 265.94 0 0 // 12th options for DV
825 1976 276.82 0 0 // 13th options for DV
900 2012 310.06 0 0 // 14th options for DV
960 2040 337.26 0 0 // 15th options for DV
1000 2142 355.69 0 0 // 16th options for DV
0 // number of real DVs

```

*DV=decision variables

Appendix A3: Sample UNIX system script “job”

```
#!/bin/tcsh

set exe = executable.exe
set inF = input.in
set seed = $1
set subF = $exe-$seed.submit

echo '#!/bin/tcsh' > $subF
echo '#PBS -V' >> $subF
echo '#PBS -N $exe-$seed' >> $subF
echo '#PBS -j oe' >> $subF
echo '#PBS -m ae' >> $subF
echo '#PBS -M ww@civeng.adelaide.edu.au' >> $subF
echo '#PBS -q hydra' >> $subF
echo '#PBS -l nodes=1,walltime=336:00:00' >> $subF

echo 'cd $PBS_O_WORKDIR' >> $subF
echo 'set localJobDir = /tmp/$PBS_JOBID' >> $subF
echo 'set outF = $PBS_O_WORKDIR/"$exe"_"$seed.out" >> $subF
echo 'cp $PBS_O_WORKDIR/* $localJobDir' >> $subF
echo 'cd $localJobDir' >> $subF
echo './$exe $seed < $inF' >> $subF
echo 'mv plot.out $outF' >> $subF

qsub $subF
```

Appendix A4: Sample UNIX system script “*runjobs*”

```
#!/bin/tcsh
```

```
set seeds = (0.111 0.123)
```

```
foreach s ($seeds)
```

```
  job $s
```

```
end
```


Appendix B

WSMGA Test Results

Appendix B1: Summary of test functions (all objective functions need to be minimized)

Appendix B2: WSMGA test results against NSGA-II

Appendix B1: Summary of test functions (all objective functions need to be minimized)

Problem	Variable bounds	Problem description	Comments
POL (2 decision variables)	$[-\pi, \pi]$	$f_1(x) = 1 + (A_1 - B_1)^2 + (A_2 - B_2)^2$ $f_2(x) = (x_1 + 3)^2 + (x_2 + 1)^2$ $A_1 = 0.5 \sin 1 - 2 \cos 1 + \sin 2 - 1.5 \cos 2$ $A_2 = 1.5 \sin 1 - \cos 1 + 2 \sin 2 - 0.5 \cos 2$ $B_1 = 0.5 \sin x_1 - 2 \cos x_1 + \sin x_2 - 1.5 \cos x_2$ $B_2 = 1.5 \sin x_1 - \cos x_1 + 2 \sin x_2 - 0.5 \cos x_2$	non-convex, disconnected
ZDT2 (30 decision variables)	$[0, 1]$	$f_1(x) = x_1$ $f_2(x) = g(x)[1 - (x_1 / g(x))^2]$ $g(x) = 1 + 9(\sum_{i=2}^{30} x_i) / (30 - 1)$	non-convex
TNK (2 decision variables)	$[0, \pi]$	$f_1(x) = x_1$ $f_2(x) = x_2$ Subject to $x_1^2 + x_2^2 - 1 - 0.1 \cos[16 \arctan(x_1 / x_2)] \geq 0$ $(x_1 - 0.5)^2 + (x_2 - 0.5)^2 \leq 0.5$	non-convex, disconnected, constrained

Appendix B2: WSMGA test results against NSGA-II

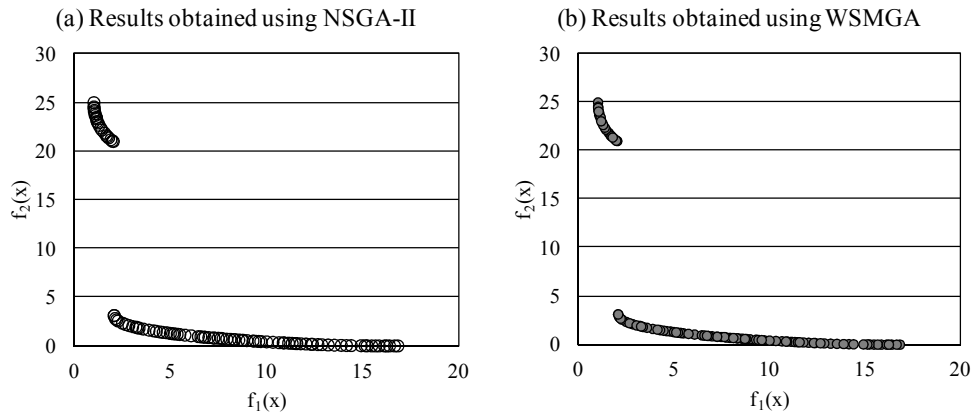


Figure B2-1 Non-dominated solutions obtained on POL (real number coding scheme)

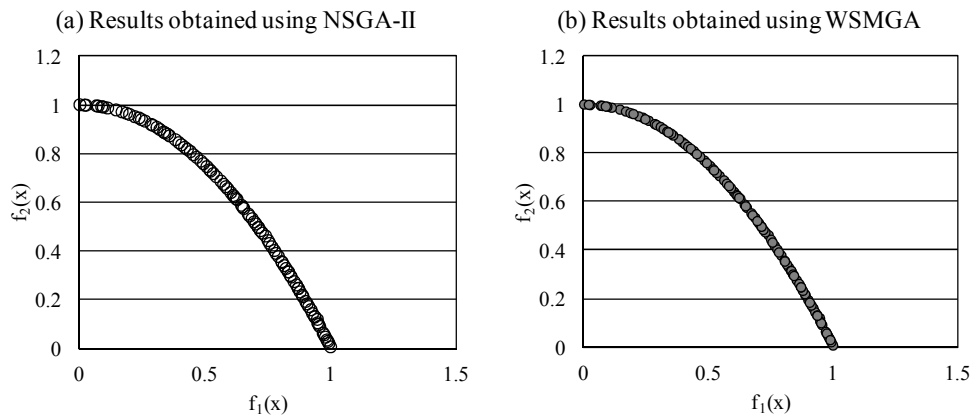


Figure B2-2 Non-dominated solutions obtained on ZDT2 (real number coding scheme)

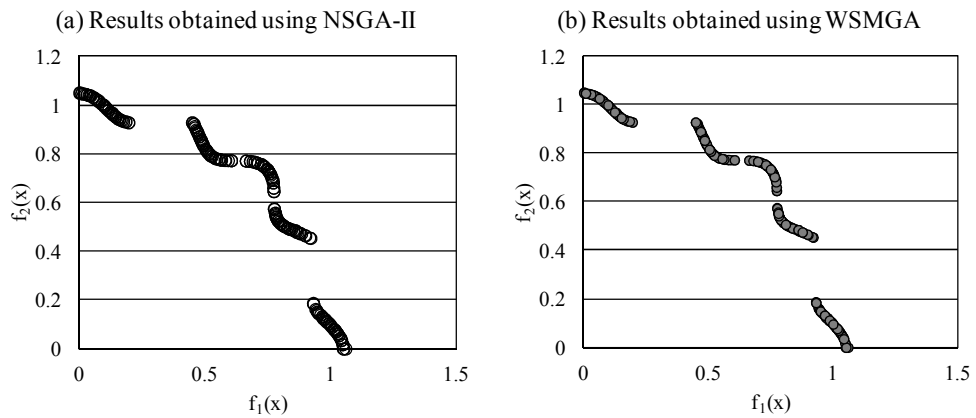


Figure B2-3 Non-dominated solutions obtained on TNK (real number coding scheme)

