Multi-Objective Optimization of Pumping Operations from Alternative Water Sources

Lisa Jane Blinco
BEng (Civil & Environmental) Hons

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Doctor of Philosophy

The University of Adelaide
Faculty of Engineering, Computer and Mathematical Sciences
School of Civil, Environmental and Mining Engineering

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Abstract

Water supply and distribution systems are an integral part of our society and can incur significant costs in their construction and operation. Many different optimization techniques have been applied to both the design and operation of traditional potable systems, which generally receive water from natural water bodies. As climate change and increasing populations prompt concerns of water security, in addition to natural harvested water supplies, alternative sources such as harvested stormwater, recycled wastewater and desalination are becoming more commonly used for both potable and non-potable supply. These systems have not been researched as extensively, particularly their operation. This thesis examines the optimisation of pumping operations in water supply and distribution systems that can include conventional potable systems as well as systems that use alternative water sources.

The major contributions of this research are presented in three publications. Firstly, a single-objective optimisation model was applied to potable water distribution systems, both hypothetical and real, for different types of pump operating regimes using the EPANET toolkit to alter rule-based controls. While minimizing pump energy costs was the primary objective, minimization of greenhouse gas emissions was also explored, including the variation of greenhouse gas emission factors for different electrical energy sources. Time-based scheduling operating strategies were found to perform better than the other operating regimes, and significant cost savings were achieved for the real-life system compared to its current operation.

In the second paper, a framework for the optimization of water supply and distribution systems that use alternative water sources is presented, along with a detailed discussion of the components and key variables. The framework connects the potential decision variables, both design and operational, the physical components of the water system to be modelled, the simulation of each potential system configuration and evaluation against objectives and constraints, and relevant policies from regulating bodies. These all exist within an optimization algorithm structure, and sensitivity analysis of uncertain variables is also discussed. Two case study systems are used to illustrate how the framework would be applied to minimize the cost of water system operations.

The final paper applies multi-objective optimisation techniques to a harvested stormwater case study system and also covers an extensive sensitivity analysis of the inputs to the system. This system has distinct winter (harvesting) and summer (irrigation) operational seasons; for the winter operation, operating rules were optimized to minimize the cost of pumping into an aquifer and to maximize the volume harvested, considering restrictions on the aquifer injection rate and pressure; during summer, irrigation scheduling was optimized to minimize pumping costs, considering the requirements for irrigation rates and amounts at various public parks and green area reserves. Results from both the optimisation and sensitivity analysis found operational cost savings if new pumps are installed, wider trigger levels are used, and certain reserves are irrigated together.

This research has produced significant overall contributions to the body of knowledge. Methodologies have been developed for optimisation of potable and alternative water sources systems, highlighting important considerations and generalizable results. For three real-life case study systems, operating strategies and infrastructure changes have been suggested to provide significant savings in the cost of pumping operations.

Statement of Originality

I, Lisa Blinco, certify that this work contains no material which has been accepted for the award of any other degree or diploma in my name, in any university or tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission in my name for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint award of this degree.

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I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

A list of works contained within this thesis is given on Page xiii.

Signed:.. .... Date:9/11/17..

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List of Publications

List of works contained within this thesis:

Publication 1 presented in Chapter 4:

Blinco, L.J., Simpson, A.R., Lambert, M.F., and Marchi, A. (2016). 'Comparison of pumping regimes for water distributions systems to minimize cost and greenhouse gases.' *Journal of Water Resources Planning and Management*, 142(6), doi: 10.1061/(ASCE)/WR.1943-5452.0000633.

See Appendix A for a copy of the final published paper.

Publication 2 presented in Chapter 5:

Blinco, L.J., Lambert, M.F., Simpson, A.R., and Marchi, A. (2017a). "Framework for the Optimization of Operation and Design of Systems with Different Alternative Water Sources." *Earth Perspectives* 4(3), doi: 10.1186/s40322-017-2.

See Appendix B for a copy of the final published paper.

Publication 3 presented in Chapter 6:

Blinco, L.J., Simpson, A.R., Lambert, M.F., and Marchi, A. (2017c). 'Optimization of Pumping Costs and Harvested Volume for a Stormwater Harvesting System.' *Journal of Water Resources Planning and Management*, submitted 25 June 2017.

List of works resulting from research associated with thesis but not contained as chapters within:

Blinco, L.J., Simpson, A.R., Lambert, M.F., Auricht, C.A., Hurr, N.E., Tiggemann, S.M., and Marchi, A. (2014). 'Genetic algorithm optimization of operational costs and greenhouse gas emissions for water distribution systems.' *16th Conference on Water Distribution Systems Analysis, WDSA 2014*, Procedia Engineering 89, 509-516, doi: 10.016/j.proeng.2014.11.246.

See Appendix C for a copy of the final published paper.

Blinco, L.J., Simpson, A.R., Lambert, M.F., and Marchi, A. (2017b). 'Formulation of the pump operations optimization problem for a harvested stormwater system.' *XVIII International Conference on Water Distribution Systems, WDSA2016*, Procedia Engineering 186, 202-209, doi: 10.1016/j.proeng.2017.03.228

See Appendix D for a copy of the final published paper.

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Chapter 1 Introduction

1.1 Research Background

Water supply and distribution systems are vital parts of today's society, ensuring the health of our communities and providing commercial, industrial and recreational benefits. These systems can have high construction and operating costs, as well as associated greenhouse gas (GHG) emissions and have long been the focus of research to make them more efficient, lower cost, and more reliable, among other objectives. Climate change is a major concern for society as a whole, and also for water resources managers. Different regions of the world will experience the effects of climate change in different ways; some areas will experience drying, while others will be wetter and the variability of rainfall is likely to increase. Climate change will also affect how rainfall is translated into runoff, as climate conditions affect the ability of soil and plants to intercept and retain water. This has major implications for how we obtain our water supply, as many regions around the world source their water from natural catchment runoff. An increasing population into the future will also put a strain on water resources. In light of this, alternative water sources are increasingly being sought out by water system managers to provide security of water supply into the future.

Some alternative sources of water, such as groundwater and imported catchment water have historically been used in conjunction with natural catchment waters. Other sources, such as harvested stormwater, treated wastewater, desalination, and aquifer storage and recovery (ASR) have gained popularity more recently. Groundwater from aquifers may be used for various applications, depending on the quality of the water. In some cases, it may already be at potable standard, or able to be further treated with little cost to obtain potable standard, and therefore be used in mains distribution systems. If it is not of potable standard, it is often used for irrigation of private gardens and public parks and reserves, especially when water restrictions are put in place to limit outdoor irrigation with mains water. Imported water is often used in areas with low local rainfall, obtaining water from other areas with higher rainfall or significant water bodies through long pipelines or canals. Harvesting of urban stormwater runoff is often applied at community scales to provide water for irrigation of public spaces. It can provide other benefits such as reducing urban runoff and creating amenity in public recreation areas. Desalination plants, while energy intensive and expensive to run, provide a climate independent source of water, and as such is a popular choice for regions prone to long or intense droughts. Recycled wastewater is another source that is also climate independent and is often used for non-potable supply, such as large scale irrigation or industrial use. Advances in treatment technologies have allowed potable standard water to be produced from wastewater, however, public perception regarding the acceptability of usage still lags behind. Stormwater harvesting and wastewater recycling systems are sometimes combined with ASR, allowing water to be stored for long periods of time in an underground aquifer and utilized when needed (without the need for large storage tanks or above-ground reservoirs that would have large construction costs and reduce amenity of public spaces). On a household scale, rainwater tanks are used to collect water from roofs generally for outdoor irrigation, however, this water may also be used indoors and for drinking. Greywater recycling systems are also gaining popularity, typically re-purposing water from showers, taps and washing machines for outdoor irrigation.

Uptake of alternative water source systems has been restricted by public and industry perception, cost, and development of appropriate technologies. While alternative sources can be, or are treated to potable quality, there is a perception that they are not suitable for drinking or human contact. The public often do not want to use alternative sources such as stormwater and recycled wastewater where there is the potential for human contact, which has restricted their application. As many systems using alternative sources are on small, decentralized (local) scales, technology to capture, treat and store water may not be available at the appropriate capacity or at a reasonable cost. The design and operation of these smaller scale systems may not necessarily be handled by people with the required expertise, and as a result the system will not perform as well as desired. Natural catchment water is a relatively low cost source, as the infrastructure to capture the water is usually already in place, the main ongoing cost is the treatment of the water. Developing alternative water source systems requires more capital infrastructure costs, and may also require higher levels of treatment or transportation over long distances, therefore increasing their ongoing costs compared to existing resources.

Energy use is one of the major contributors to ongoing costs in water distribution systems (WDSs). Reducing their energy use starts in the design phase, investing more in capital infrastructure may allow the system to operate with less energy requirements and therefore reduce ongoing costs. There is usually a trade-off between capital and ongoing pumping costs that should be explored to find the best compromise for a particular system. For existing systems, energy efficiency can be improved using strategies such as leak identification and repair or system maintenance as well as by altering the pump operating rules of the system. Variable speed pumps (VSPs) can also be used to adjust the pump operating points for different system conditions and save energy by reducing pumping heads and flows. In systems where excess pressure energy occurs, it may be recovered using mini-hydro systems or pumps and turbines. Pump operating strategies can broadly be split into trigger levels (based on the amount of water or level in a storage) and scheduling (based on the time of day or week). Electricity tariff periods should be considered when optimizing pump operating rules, and different rules may be required for different seasonal conditions.

While engineering judgement can be used to guide the design and operation WDSs successfully, there is often a large number of decisions to be made and multiple objectives. Formal optimization algorithms are very useful in order to efficiently find solutions that will improve the performance of the system with regard to the objectives. They do not necessarily need to analyse all possible solutions to find the optimal solution(s). When multiple objectives exist, care needs to be taken when determining the objective function(s). Multiple objectives can often be combined into one function, however, this requires the normalization of objective values and the relative importance of each objective needs to be decided upon. There are many multi-objective optimization algorithms available, that are able to deal with each objective function separately, allowing them to retain more meaning. Engineering judgement should always be used in conjunction with optimization, as it can help to limit the search space of the problem and ensure the optimal solutions found are reasonable. Simulation of the system prior to optimization is very important as it provides an understanding of how the system works and helps these engineering judgements to be made. Genetic algorithms (GAs) are a robust and efficient optimization method that have been used extensively for the design and operation of WDSs. They are a population based technique, which means they evaluate multiple solutions at once and use operators based on natural selection principles to gradually improve the performance of the population through successive generations. Given the complexity and cost constraints of alternative water source systems, optimization methods such as GAs are very useful to improve their performance and make them more cost comparable to traditional WDSs.

1.2 Research Objectives

The overall aim of this research is to develop and apply methodologies for optimizing complex pumping operations to systems that use alternative water sources; this is split into six objectives:

Objective 1. To develop a framework to optimize alternative water system pump operations for multiple objectives including minimizing cost and maximizing volume harvested.

Objective 2. To apply the use of new rule-based controls in a modified EPANET2 programmer's toolkit to optimize complex pump operational strategies using a combination of trigger levels and scheduling, and variable trigger levels.

Objective 3. To optimize pumping operations and irrigation scheduling for short time horizons for systems using harvested stormwater with aquifer storage and recovery and multiple pumping stations.

Objective 4. To demonstrate the importance of performing detailed simulation analysis of water systems in order to better understand the system and to inform optimization of the system.

Objective 5. To analyse the sensitivity of optimal pump operations to changes in streamflow (system inflow) and system design in a stormwater harvesting system.

Objective 6. To minimize GHG emissions from pump operations where operational characteristics are considered as decision variables and characterize trade-offs between optimal cost and optimal GHG solutions for these problems.

As shown in Figure 1.1, the six objectives are connected and each of the Chapters in the main body will contribute to multiple objectives. The development of a framework in Objective 1 will inform the execution of Objectives 3 and 6. Rule-based controls in a modified EPANET2, which are specifically included within Objective 2, will also be used in Objectives 3 and 6. The detailed analyses in Objectives 4 and 5 will inform the optimization of a harvested stormwater system in Objective 3. Objectives 2 and 6 represent a gap in the current research on optimization of pump operations in potable WDSs and are investigated in the Chapter 4 for two potable WDS case studies. Chapter 5 investigates Objective 1, and how the current methodologies used for potable WDSs need to be altered to take into account additional complexity and processes that come with the use of alternative water sources. It also discusses variables that should be taken into account in sensitivity analyses of water systems, such as in Objective 5. Objectives 3, 4 and 5 are addressed in Chapter 6, which details the analysis and optimization of pumping operations in a harvested stormwater and ASR case study.

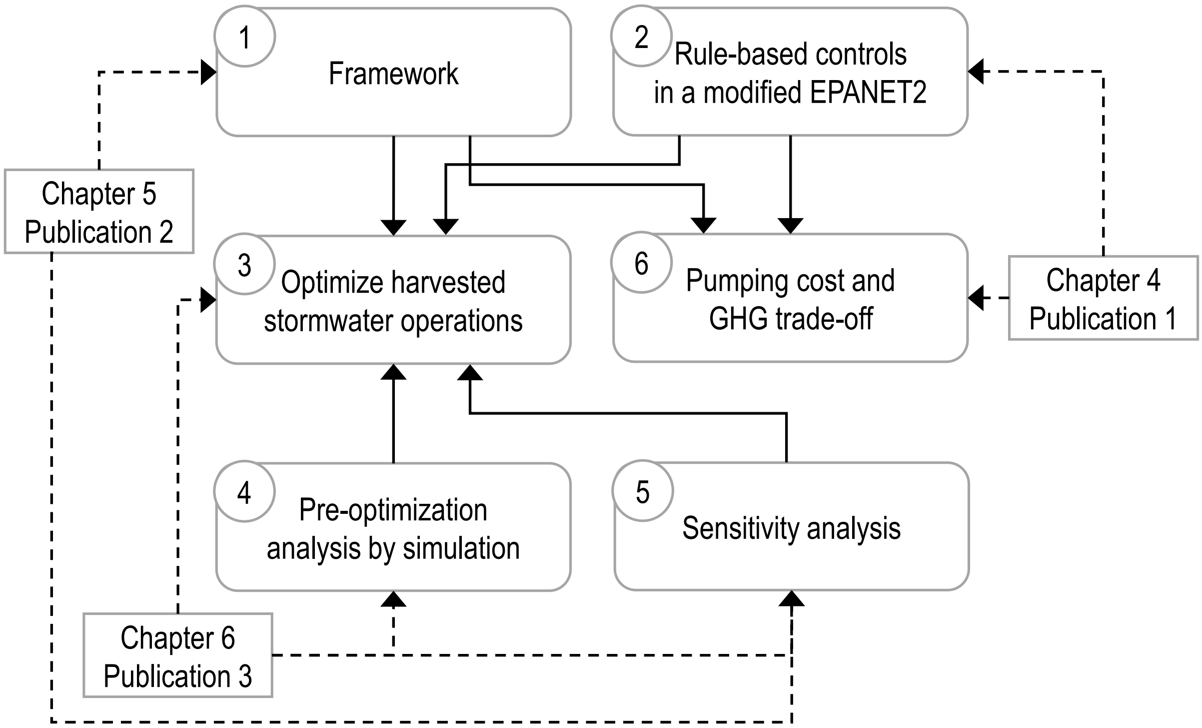


Figure 1.1: Connections between the six objectives and chapters in this thesis

1.3 Thesis Outline

This thesis is presented as a collection of three journal publications that were developed along with the research undertaken and is arranged in seven chapters. **Chapter 2** presents a detailed review of the relevant literature on the topics of pumping operations, alternative water sources and genetic algorithm optimization. The three publications that make up this work are summarised in **Chapter 3**, which demonstrates how the publications are linked to each other and to the research objectives identified in Section 1.2.

Chapter 4 presents the first publication (Blinco et al. 2016a): 'Comparison of pumping regimes for water distribution system to minimize cost and greenhouse gas emission,' published in the *Journal of Water Resources Planning and Management*. In this paper, five different types of pump regimes were explored; lower and upper trigger levels, reduced upper trigger level, combined trigger levels and scheduling, variable trigger levels, and variable speed pump (VSP) scheduling (Objective 2). These regimes were optimized and compared for two potable case study networks, considering objectives of minimizing pump energy costs and minimizing GHG emissions from pumping (Objective 6).

The second publication (Blinco et al. 2017a) is in **Chapter 5**: 'Framework for the optimization of operation and design of systems with different alternative water sources,' published in *Earth Perspectives*. This paper presents a methodology for optimizing water supply and distribution systems that use alternative water sources such as harvested stormwater, imported water (from adjacent catchments), groundwater and desalination (Objective 1). The framework details the different design and operational options, the water and electrical energy infrastructure, the relevant government policies, the simulation model and evaluation options and how these components fit within and optimization algorithm. Variables that may be considered in sensitivity analyses of water systems are also discussed (Objective 5) and two case studies are used to demonstrate the application of the framework.

Chapter 6 contains the final publication (Blinco et al. 2017c): 'Optimization of pumping costs and harvested volume for a stormwater harvesting system,' submitted to the *Journal of Water Resources Planning and Management*. This paper demonstrates the application of the framework methodology from the second publication, and the pumping operations optimization from the first paper to a harvested stormwater system (Objective 3). The first part of the paper shows a detailed analysis of the current operation of the system and possible operation under different design scenarios (Objective 5). Optimization of the system is then presented and the importance of both the pre-analysis and optimization procedures is discussed (Objective 4).

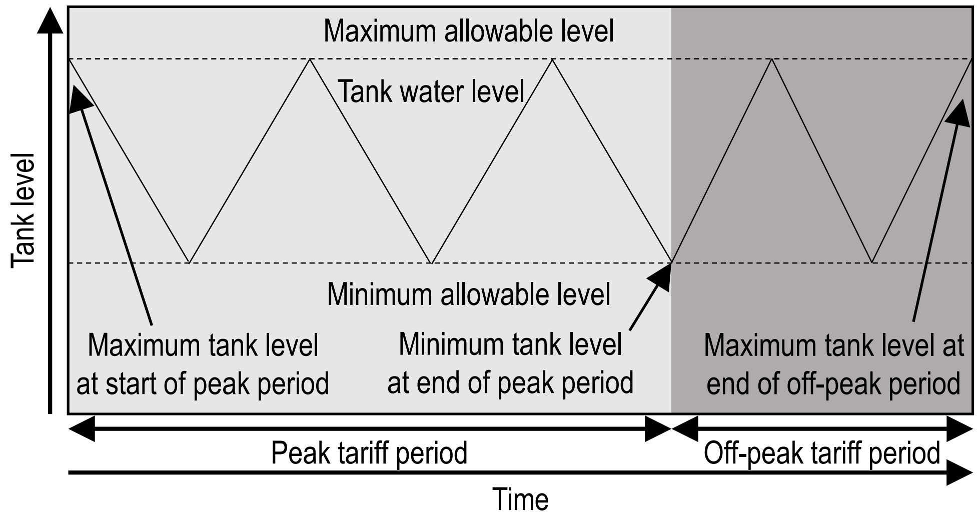
The main conclusions and contributions of this research are presented in **Chapter 7**. This chapter also summarizes the limitations of the research and suggested future directions in this study area.

Chapter 2 Literature Review

2.1 Pumping Operations

The operations stage of a WDS is a significant contributor to life-cycle energy use (Stokes and Horvath 2005) and therefore often represents a significant cost to water utilities (Boulos et al. 2001). Optimizing how WDSs operate, particularly in terms of pumping controls, can therefore have a significant impact on reducing cost and energy use for water system managers. Other strategies for recovering or reducing energy use in WDSs include energy dissipation by mini-hydro systems or pumps as turbines (Carravetta et al. 2013b, Fecarotta et al. 2015), leak reduction (Giustolisi et al. 2013) and system maintenance or repairs. Cabrera et al. (2016) highlight the importance of examining 'topographical energy', that is excess pressure at nodes of low elevation, in a network. Where large amounts of topographical energy exist, pumps as turbines can be used to recover some, or pressure reducing valves can be installed to reduce leaks. As well as cost, there are other objectives that may improve the operation of WDSs, such as water quality (Stokes et al. 2012a), pump switches or maintenance cost (Lansey and Awumah 1994, López-Ibáñez et al. 2005), system effectiveness (Carravetta et al. 2013a), and resilience (Prasad and Park 2003). The design of the system also has a significant impact on the ongoing energy use and there is often a trade-off between initial construction costs and ongoing operational costs. Networks with smaller diameter pipes have increased friction losses compared to those with larger diameter pipes, and hence require more energy during pumping operations (Wu et al. 2011). This means that while smaller diameter networks are generally less expensive to construct, they are more expensive to operate than larger diameter networks and there will be a different compromise between capital and operational costs for different systems. For existing system rehabilitation, installing newer, smoother pipes, or replacing pumps with more efficient ones, usually may incur a significant capital cost, however, these actions can reduce ongoing operational costs (Fernández Garciá et al. 2016). Elevated storages in a network used to store water judiciously, can be used to reduce the amount of pumping in peak periods, therefore reducing energy costs (Jin et al. 2015). Where energy sources with higher air pollutant emission rates are used as top-up during times of peak electricity demands, the environmental impact of pumping can also be reduced (Jin et al. 2015). An initial step to reducing the energy use of a WDS is to conduct an energy assessment (Cabrera et al. 2010, 2015) to determine which parts of the system should be the focus for removing energy inefficiencies. The research presented in this thesis is focussed on optimizing energy cost of pumping operations.

There are two main types of pumping controls; trigger levels, which turn pumps on or off depending on the level or volume in a storage, and scheduling, which requires pumps to be on or off at particular times of the day. Both have been investigated extensively by optimization to reduce costs of WDS operation. An important result is the benefit of pumping only in off-peak (lower cost) electricity tariff periods, investigated in Mäckle et al. (1995) for pump scheduling and Kazantzis et al. (2002) for combined trigger levels and pump scheduling. Both of these studies found that optimal solutions occurred when tanks were full at the start of the peak tariff period, and at their minimum allowable level at the end of the peak tariff period (Figure 2.1). This meant that the minimum possible amount of pumping would occur at the expensive tariff rate, and the maximum possible amount of pumping at the lower cost tariff rate. For systems with multiple pumps, the most efficient pumps should be used during the peak (expensive) electricity tariff period, and the least efficient during the off-peak period (Mäckle et al. 1995). Two type of alterations to typical lower and upper trigger levels were examined in Kazantzis et al. (2002); adding a scheduled pump start and pump stop, or using a reduced upper trigger level. A pump stop can be scheduled before the end of the peak period, to ensure the water level in the tank is at the minimum allowable level at the end of this period. Likewise, a scheduled pump start before the end of the off-peak period, can ensure the water level is at the maximum allowable level for the start of the peak period. A reduced upper trigger level applied over the peak tariff period will limit the static head of the system, and therefore less energy will be required for pumping. At a specified switch time during the off-peak period, the reduced upper trigger level will be removed so that the tank can fill before the start of the peak period. The solution presented in Kazantzis et al. (2002) optimized the reduced upper trigger level, a scheduled pump stop, and the switch time for the reduced level. Lower and upper trigger levels were used in the solution, however, they were not optimized.



Note: it is difficult to achieve these tank level criteria using only a lower and upper trigger level

Figure 2.1: Example of tank water level with efficient pumping in WDSs (adapted from Kazantzis et al. (2002))

While peak and off-peak tariffs are an important consideration for cost minimization, in order to reduce GHG emissions, it may be better to pump steadily throughout the day with a VSP to reduce the velocity of flow in the pipe and hence reduce the friction loss (Simpson 2009). Lingireddy and Wood (1998) and Wu et al. (2011) have demonstrated the benefits of using VSPs to reduce both energy use and GHG emissions in WDSs. They are particularly effective in smaller diameter networks with high friction losses, as VSPs run at reduced flows, they can reduce the friction losses through the system (Wu et al. 2011). The relative speed of VSPs may be a decision variable in an optimization formulation. In systems controlled by trigger levels, the VSP speed at discrete time intervals during the day could be optimized, which would be overridden by the trigger levels if they require the pump(s) to be off. The inclusion of VSP decision variables in pump scheduling optimization depends on the form of the schedule. Pump scheduling may be structured in two different ways; firstly using a discrete on or off (1 or 0, or VSP relative speeds) at set time intervals (say every hour in a 24 hour simulation), or represented as continuous values with set times (for example, 8:15am or 12:35pm) to turn pumps on or off. Continuous representation is more flexible, however, can produce a high proportion of infeasible solutions depending on the coding of the optimization algorithm (Sadatiyan Abkenar et al. 2015) and would require additional decision variables to set the speed of VSPs.

Many studies into pump operations of WDSs use EPANET2 hydraulic simulation software to determine energy use and cost of the systems (for example Kazantzis et al. 2002, López-Ibañez et al. 2005, and Fernández Garciá et al. 2014). Gómez et al. 2016 examine the limitations and errors in EPANET with regards to energy, which should be considered and addressed if needed when using the software. Three major issues and four minor issues were raised. The first major issue was the error in calculating the efficiency of VSPs operating at a reduced speed and this research utilized code to correct this error (Marchi and Simpson 2013). The second major error is that ‘natural’ energy (from elevated tanks and storages) is ignored, which may be important for performing energy audits (as in Cabrera et al. 2010) or when considering different system layouts. This thesis is focussed on operations of existing systems (no layout changes are considered) and minimizing electrical energy use, and thus this limitation is not relevant to the current work. The final major issue raised is that the energy use and costs presented in the EPANET2 interface are scaled to a 24 hour time period, even if the simulation is run for a different length of time. When connected to an optimization algorithm, the energy cost can be calculated outside of EPANET2 based on the energy use in each time step, thus avoiding the problem.

Two of the minor problems relate to the specification of electricity price tariffs, in particular for systems with multiple pumping stations. Tariff patterns can be specified for each pump individually in order to take into account changes to electricity prices over the simulation period (typically this represents daily or weekly peak and off-peak tariffs). The peak power demand charge, however, is usually set for the whole system, not each pump, which may be limiting. If a peak power demand charge applies to only some pumps, or differs across pumps, external code (outside of EPANET2) may need to be used to accurately compute the cost. The energy efficiency of variable speed drives (VSDs) and electric motors was another issue raised, as EPANET2 considers only the pump efficiency. Both the motor and VSD efficiencies are typically much higher than pump efficiencies, and if the pump speed is reduced to no less than 75% of full speed, the pump efficiency needs to be altered (Sârbu and Borza 1998). If no VSPs are used, the motor and VSD efficiencies do not change (whereas the pump efficiency may change with the pump operating point), and as such will be the same for all operating strategies. While the energy costs computed will not take into account motor and VSD efficiencies, they can still be compared between different operating strategies as the effect of these other efficiencies would be the same for each strategy. The final minor issue raised was the energy intensity (the energy used per volume), which is calculated based on the volume supplied by pumps rather than the volume received by consumers (therefore ignoring leaks). For systems with leaks, external code (to EPANET2) could again be used to work around this problem.

A recent advance for EPANET2 is the additional capability of the programmer's toolkit developed by Marchi et al. (2016b) to allow rule-based controls to be optimized. Previously, only simple controls (with only one condition) and pump scheduling could be optimized through EPANET2. Optimization of rule-based controls (as implemented by Marchi et al. (2016b)) provides much greater flexibility and complexity to be considered in pump operations optimization. Rule-based controls in EPANET2 are made up of many different components, including logical operators, EPANET2 objects (tanks, pipes and so on) and their identifying indices, hydraulic and system variables (for example pressure, flow, clock-time), relational operators, status (open or closed pipes, valves or pumps) and values of the variables. Using the new EPANET2 modified toolkit from Marchi et al. (2016b), each of these components can be optimized individually, or the entire rule can be optimized as a whole.

In WDS simulation and optimization, it is often assumed that water is available in an upstream storage reservoir. This separates the distribution system from the supply system, and does not consider uncertainty in supply. The main source of uncertainty for WDSs is therefore in the consumer demands, which naturally fluctuate daily, weekly and seasonally, and will also vary into the future with population and climate change. Most studies incorporate a daily diurnal variation in water demands, however, seasonal variation is also an important consideration. Paschke et al. (2001) optimized tank trigger levels considering different water demands in different seasons. During summer, when demands are higher, the optimal trigger levels kept the water level higher in the tank, whilst during winter, the water level was allowed to be lower in the tank, as demands were reduced. Basupi and Kapelan (2015) used Monte Carlo simulation to find optimal WDS design and operation that was flexible to future changes in demand. They assumed that the demand follows a normal distribution, with the mean and standard deviation increasing over time to represent greater future uncertainty. Stochastic programming was used by Goryashko and Nemirovski (2014) to determine optimal robust pump schedules; that is, operations that are feasible for all demand realisations. In their methodology, complex systems with non-linear hydraulics need to be reduced down to equivalent linear systems as they used linear programming for optimization. Eck et al. (2015) examined how estimates of demand mean and covariance can be produced from smart meter data, and then used to develop demand scenarios for robust valve operation optimization. They found that incorporating only a small number of scenarios could give significant improvement in pressure constraint violation with little cost increase. Marques et al. (2015) used a 'real-options' approach to consider multiple future demands with two objectives; the first was the combination of economic costs and GHG emissions (using a carbon price), and the second was the level of service. For their case study, the 'real-options' method considered the probability of different possible WDS adaptations at three stages over a 60 year horizon through a decision-tree structure.

2.2 Alternative Water Sources

Water is increasingly being seen as a fundamental and finite resource (Bogardi et al. 2012) and alternative water sources are being used to supplement potable demand as climate change and population growth highlight water security issues (Fielding et al. 2015). Decentralised harvested stormwater systems (often managed by local councils in Australia) and household greywater recycling systems are popular for supplying non-potable demands such as household gardens and public green spaces (Naylor et al. 2012). At household scales, installation of rainwater tanks is increasing in popularity (Campisano and Modic 2012), which reduces consumption of water from utilities and decreases stormwater runoff from residential areas. The millennium drought prompted several Australian cities to construct desalination plants (King et al. 2012), providing a climate-independent source of water. Use of desalination is also increasing in other areas of the world, however is not always the most cost effective or environmentally sustainable source of water (Miller et al. 2015, Becker et al. 2010). Recycling of wastewater and greywater on community and regional scales is also gaining popularity, often for non-potable applications (Muga and Mihelcic 2008, Oron et al. 2014), however in some cases it may also be used for indirect potable supply (Rodriguez et al. 2009). Recycling wastewater for re-use at the same site is becoming common, particularly in industrial settings (Mariano-Romaro et al. 2007). Imported water refers to water transported through pipe or canal systems from different regions and is already used in many major cities, for example, Adelaide (from the Murray River) and Los Angeles and San Diego (from the Colorado River). This typically requires a lot of energy even in well-designed or optimized systems, because of the distance the water must travel and the height it needs to be lifted (Water in the West 2013).

An alternative strategy to supplementing potable supplies with other water sources is demand management to reduce per capita demand (for example, Freidman et al. 2014). Such strategies should be considered under future climate change and population growth (Dawadi and Ahmed 2013). This can take on forms such as mandated outdoor irrigation times, water efficiency standards for shower heads, taps, toilets and appliances, and awareness campaigns to encourage the public to use less water (Berhanu et al. 2016). Smart metering, which is becoming more commonly used by water utilities, can provide information for demand management, such as data for early leak detection and demand pattern classification and forecasting (McKenna et al. 2014). Each of these alternative sources, along with demand management strategies, play a role in delivering water security to towns and cities around the world. Communities also value other benefits of alternative water sources, for example, improved hydraulic function and water quality from stormwater schemes (Londoño Cadavid and Ando 2013). Negative public perception can come from a low awareness or understanding of associated risks (Hwang et al. 2006) and different types of sources will have different levels of acceptance by the public (Feilding et al. 2015). One of the main barriers to uptake of alternative source systems from a water system manager's perspective is the cost of running and maintaining the system (Dobbie and Brown 2012, West et al. 2016).

The inclusion of alternative sources in water supply system increases the complexity of system simulation and the corresponding optimization problem (Paton et al. 2014). Marchi et al. (2016a) optimized the design of a harvested stormwater system, taking into account climate change and externalities such as reduced runoff to receiving water bodies and reduced urban stream flows. They highlighted the need to consider the supply and distribution sides of the system together, the use of longer simulation times and the inclusion of rainfall and evaporation scenarios as factors that increased the simulation complexity compared to traditional WDSs. Optimization of alternative water source systems often considers objectives and constraints other than just construction or ongoing costs. In groundwater systems, land subsidence is an important consideration and can be reduced by extracting water intermittently (Wang et al. 2009). Water quality may need to be considered, such as in Labadie et al. (2012), which optimized releases from multiple stormwater reservoirs to reduce pollutant loadings on downstream waters. When alternative water sources are used to supplement potable supply, the amount of water than can be harvested from the system is a key variable. It may be the single objective of an optimization problem (for example, Eusuff and Lansey 2004), or combined in a multi-objective optimization with design or operational costs and other objectives (for example, Karamouz et al. 2007, McArdle et al. 2011, di Matteo et al. 2016). Tsai et al. (2009) optimized pump schedules in an integrated surface and groundwater system for six objectives (combined into one weighted objective function); minimum pump energy use, minimum pressure violation, minimum tank residence time, minimum tank level deviation, minimum weekly drawdown and maximum tank reliability. Through altering the weightings of the different objectives, they found that some of the objectives were interrelated and some could act as surrogates for others, with energy use and pressure violation being the most important. Factors such as pressure violation and tank level balancing are often included in optimization problems as constraints, however they can also be formulated as objectives.

Sustainability is often a key concern in alternative water source systems and can be evaluated using a 'triple bottom line' of economic, environmental and social criteria. Kang and Lansey (2012) optimized life-cycle cost (economic), GHG emission (environmental) and system reliability (social) of a dual-pipe network using recycled wastewater for non-potable supply. In comparison to single-pipe systems, the dual-pipe systems were more expensive, however they performed better in terms of the environmental and social criteria. McArdle et al. (2011) also considered three objectives; minimizing present-worth or capital and ongoing costs (economic), maximising the amount of water harvested from a stormwater scheme (environmental benefits to urban water system and increased water security), and minimizing the size of a storage reservoir in a public park (therefore minimizing the impact on the social amenity of the park).

Due to the complexity of WDS simulation and optimization, and the additional considerations for alternative water sources, many different frameworks, methodologies and decision-support tools have been developed. Stokes et al. (2014) presented a framework for the design and operation of WDSs using traditional water sources. The focus of this framework was the water-energy nexus, with different energy sources and GHG emissions factors included for consideration, and cost and GHG emission objectives. There was no consideration of the supply side of the WDS or alternative water sources. A framework by Ashbolt et al. (2014) can be used to optimize operating plans for water systems using surface water, groundwater, desalination, recycled wastewater and imported water. Multiple objectives are incorporated by weighting their importance and multiple replicates of inflows can be used for uncertainty analysis. The design of the system is not included in the decision variables and the operations consider the levels in main reservoirs that trigger different water sources to be used, not the operation of pumps and smaller storages within the individual water source systems. Harvested stormwater systems have not often been included in these frameworks, however, the methodology in Marchi et al. (2016a) optimizes the design of ASR stormwater systems with consideration of future climate scenarios. Externalities are included in the analysis, such as reduced volume of stormwater to treat before discharge, reduced peak flows (and therefore reduced capital expenditure), and increased economic value of properties near stormwater schemes. For the case study system in South Australia, the yield and net present value of the scheme would both be decreased under future climate, however, they acknowledge that urban stormwater runoff is likely to be less affected by a drier climate than rural surface water runoff. Water saving and demand management strategies were incorporated into a decision-support tool developed by Makropoulos et al. (2008) and Rozos and Makropoulos (2013). This model was a demand-oriented mass balance simulation, not incorporating hydraulic or hydrologic modelling, for the entire water cycle including wastewater streams.

As alternative water sources are important parts of climate change adaption strategies, frameworks developed for these sources have often been focussed on water security in future climates. Paton et al. (2014) produced a methodology for evaluating water source alternatives under multiple future scenarios to minimise cost and maximise water security. For nine water source alternatives with different combinations of surface water, harvested stormwater, desalination and rainwater tanks, these objectives were evaluated by simulating them over different future demand and climate scenarios and different stochastic time series' for the years 2030 and 2050. Beh et al. (2014) also investigated different water source alternatives, however were focussed on how their implementation is sequenced. Two different sequencing approaches were applied to the same case study and water source types used in Paton et al. (2014); the first method was to optimise the sources used at each decision stage in sequential order, the second method optimised the sources used in the final decision stage first, and then scheduled the implementation of those sources. Neither of these studies considered the detailed design or operations of the alternative water source systems. Chung and Lansey (2009) also developed a methodology for optimal planning of WDSs, where the available sources were groundwater, surface water and recycled wastewater. The systems were analysed over a 20 year time period, with demands increasing in line with expected population growth and no changes to climate conditions. Chung et al. (2008) present a mathematical model for water supply management and applied it to a hypothetical case study system to investigate the differences between decentralized and centralized systems. Multiple sources, uses, transportation and treatment systems can be incorporated for surface water, groundwater and recycled wastewater sources. This does not incorporate optimization of the system, only analysis of different systems or scenarios proposed by the user. The decision-support framework from Cai et al. (2015) can be used for strategic planning for drought mitigation in agricultural systems under climate change. A range of options such as infiltration ponds, parallel terraces, irrigation triggering thresholds and irrigation water sources are available to be implemented in multiple decision stages. The performance of each possible solution is evaluated based on three objectives; minimizing cost of drought preparedness and mitigation, maximising agricultural production, and maximizing low flows for ecosystem conservation.

2.3 Genetic Algorithm Optimization

GAs are a robust and efficient optimization method that have been applied to many different applications, including various water resources problems (Nicklow et al. 2010). From their first application in 1989, Goldberg noted their desirability compared to traditional optimization techniques stemmed from four significant differences; they work with coded representations of the solution parameters, not the parameters themselves; they search from a population of points, not a single point; they use performance information as the objective function, not derivatives or other system equations; and, they use probabilistic rather than deterministic transition rules. Since then, they have been shown to perform very well in water resources applications in many studies. Simpson et al. (1994) compared GAs to other optimization techniques for pipe network design, and found that they performed better in regards to final solution optimality and iterative efficiency. Wang et al. 2015 compared the performance several different multi-objective evolutionary algorithms (of which GAs are a sub-set). They found GAs, in particular the non-dominated sorting algorithm II (NSGA-II, introduced in Deb et al. 2002), performed well compared to the other algorithms for twelve benchmark WDS design problems. Many different GAs have been developed, and NSGA-II has been shown to perform well compared to other algorithms on multiple occasions (Barán et al. 2005, Reed et al. 2013, Wang et al. 2015).

The basic premise of GAs is that they find (near) global optimal solutions using processes akin to natural selection. Solutions are coded as ‘strings’ which contain decision variables. Each solution has a different set of decision variable values. An initial population of solutions is generated at random, and the ‘fitness’ of each solution evaluated using the objective function(s). Solutions then undergo processes of selection, crossover and mutation to produce the next generation (Figure 2.2). The fitness of each solution is evaluated again, and the process repeated for a number of generations to converge to the optimal solution (Goldberg 1994). The selection process randomly pairs up solutions and takes the fittest (best, for example, minimum cost) solutions through to the next step, this is done twice, so that the number of solutions in the population remains the same. This means that two copies of the best solution and zero copies of the worst solution will go through to the next step. All other solutions will have either zero, one or two copies go through, depending on their fitness values and which solutions are paired together. The solutions that make it through the selection process are then randomly paired again for crossover. Each pair may or may not actually undergo the crossover process, depending on the probability of crossover, which is generally between 70 and 100%. Pairs that are selected for crossover, will then have parts of their string swapped from a randomly selection position. The final operator is mutation, which occurs with a much lower probability, generally less than 10%. Each gene in the string may or may not be changed to a random value depending on this probability of mutation (Simpson et al. 1994). Constraints on the system (such as minimum pressures for WDSs) are generally taken into account in one of two ways. The first way is to add a penalty cost to the objective function, with the magnitude of the cost being relative to the magnitude of the constraint violation (this could be in a linear, exponential or other type of function). The second way is by a process called constraint tournament selection (Deb et al. 2002, Wu et al. 2010b). When two solutions are paired up during selection, there are three possible scenarios; firstly, that both solutions are feasible, in which case the one with higher fitness will go through; if one solution is feasible, and one infeasible, the feasible solution will be selected regardless of their fitness values; finally if both solutions are infeasible, the solution that violates the constraints least is selected. This type of selection removes the need to determine an appropriate for a penalty cost value or formula.

When there are multiple objectives, the fitness evaluation and selection process is more complicated. Multiple objectives may be combined into a single objective function using weights to normalize the values and place different levels of importance on different objectives. Alternatively, each objective may have its own objective function, which are then treated separately. This means that a different selection method is required to take into account the different objectives. One such method is non-dominated sorting; when a multi-objective algorithm is used, multiple optimal solutions are found, termed ‘Pareto’ optimal or ‘non-dominated’ solutions. Rather than converging to a single global optimum, the algorithm converges to a Pareto front (for two objectives, for three objectives it is a surface). Solutions on the Pareto front cannot be improved in all objectives at the same time (Kasprzyk et al. 2012). For example, in an optimization to minimize pumping cost and maximize the volume harvested by a water system, to decrease the cost of a solution, the volume harvested must also decrease (the inverse of the volume harvested increases), and to increase the volume harvested, the cost must also increase (Figure 2.3). Rather than comparing fitness values of potential solutions as in a single objective algorithm, non-dominated sorting compares solutions based on their 'rank', which is determined by how many other solutions they are dominated by. If two solutions have the same rank, the 'crowding distance' will be compared in order to preserve variety in the optimal front (Deb et al. 2002). NSGA-II was used in this research, and in addition to the basic GA process shown in Figure 2.2, it implements non-dominated sorting, crowding distance comparisons and constraint tournament selection (Figure 2.4).

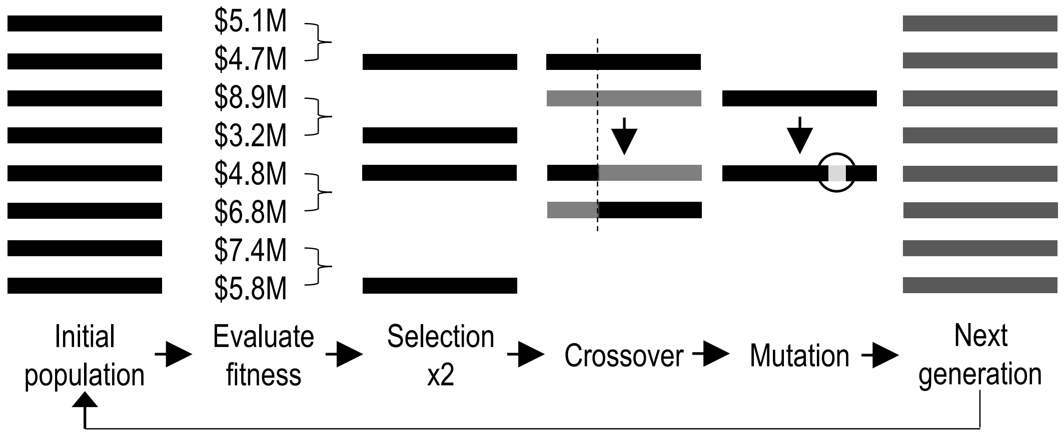


Figure 2.2: Schematic of the Genetic Algorithm process

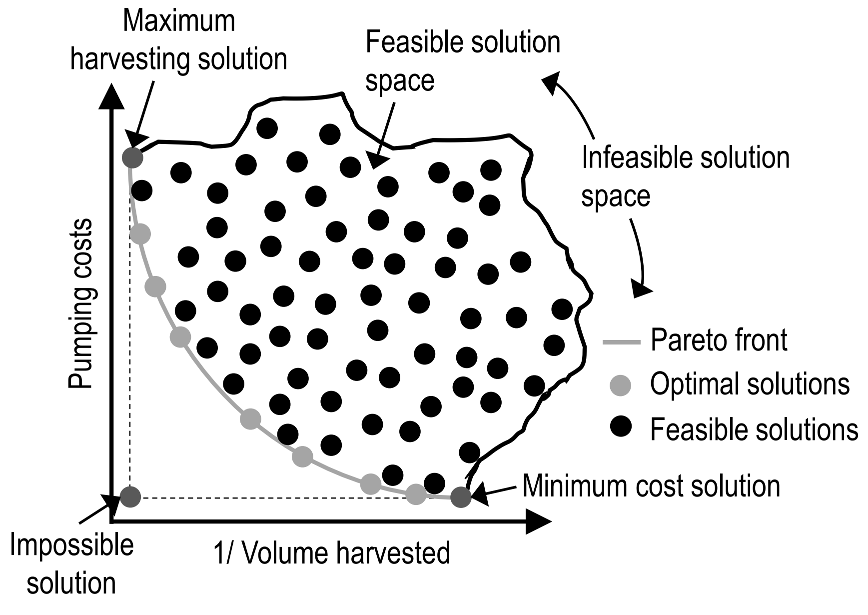


Figure 2.3: Example of a Pareto front

Comparisons of multi-objective and single objective optimization algorithms applied to the same problem have been made by Savic et al. (1997) and Wu et al. (2010b). Savic et al. (1997) used GA optimization to find optimal pump schedules to reduce energy cost and pump switches (a surrogate for maintenance costs). Wu et al. (2010b) optimized both energy cost and greenhouse gas (GHG) emissions in WDS design. Single-objective algorithms may be able to find some or all of the Pareto optimal solutions from a multi-objective algorithm applied to the same problem. This can be achieved by using different weights for the different objectives in the single objective function. The problem with this, however, is that some information about the trade-offs between objectives is lost, and the modeller must make decisions about the relative importance of each objective before starting the optimization. When a multi-objective algorithm is used to develop a Pareto front, the trade-off information can be supplied to the decision maker, and the relative importance of each objective examined after the optimization is performed (Savic et al. 2002).

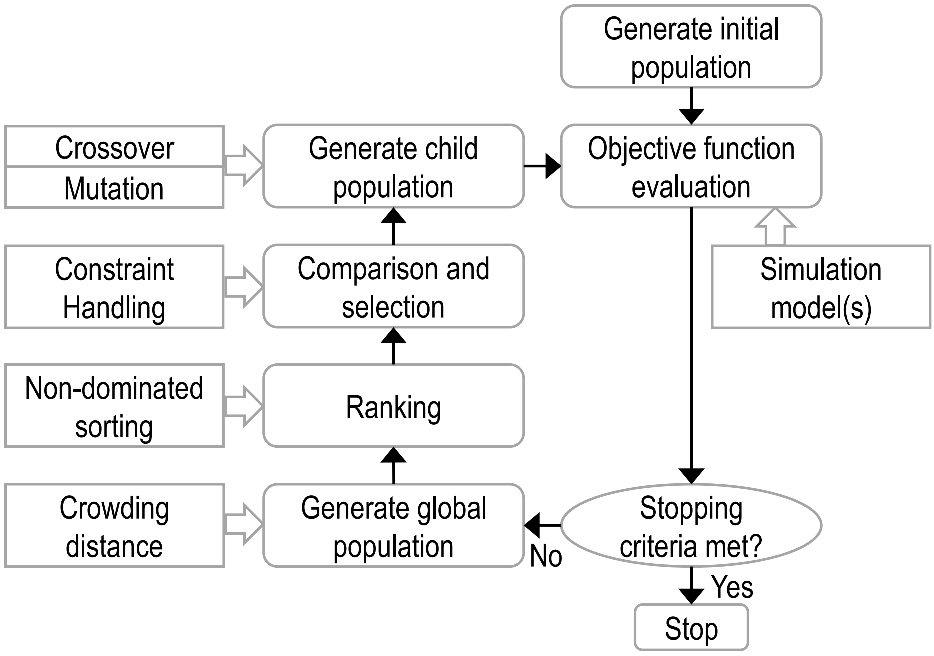


Figure 2.4: Schematic of the NSGA-II process (adapted from Wu et al. 2010b)

The primary objective for many optimization problems, in any field, is the minimization of cost, either initial, ongoing or life-cycle. In water resources applications, other objectives such as system reliability, water quality and environmental factors have been investigated. As climate change becomes an increasingly serious problem for society, reduction of GHG emissions from many different industries, including the water industry, becomes more important (Stokes et al. 2014). Stokes and Horvath (2005) undertook a life-cycle energy analysis of two WDS case studies to determine which life-cycle stages and which water sources (selected from imported, treated wastewater and desalination) used the most energy. Production of electrical energy for WDSs was the biggest contributor to global warming potential throughout the life-cycle. They also highlighted the importance of the assumed energy mix or emissions factor used in GHG analysis. Economic costs and GHG emissions may be combined into a single objective function using a carbon cost (for example, Marques et al. 2015), which may or may not be informed by government policy. It is very difficult, however, to calculate the true cost of carbon emissions (Vale 2015), and as such a multi-objective algorithm may be more appropriate. Wu et al. (2012a) investigated the sensitivity of trade-offs between cost and GHG emissions of WDS design to the assumed electricity tariff and energy generation mix. The assumed electricity tariff had a significant effect on the total economic costs and the optimal solutions found, while the emissions factors affected only the GHG emissions and not the optimal solutions on the Pareto front. If a constant GHG emissions factor is used, then the amount of GHGs emitted is directly proportional to the electrical energy use and thus minimization of energy use can be a surrogate for minimization of GHG emissions, such as in Ramos et al. (2011). GHG emissions factors are variable with time, however, as the energy generation mix changes in both the short term (particularly with renewable source reliant on weather conditions) and in the long term. An example of this is shown in Figure 2.5 for the variation in solar photovoltaic output over one day. Generation of electricity from solar photovoltaic panels produces less greenhouse gas emissions than traditional fossil fuel sources. As such, when solar photovoltaic output increases during the middle of the day, overall emission factors for a region decrease. Energy used in the middle of the day therefore results in less GHG production, and as such energy cannot always be used as a direct surrogate for GHG emissions. Time-dependent emissions factors were considered in Stokes et al. (2012b) in the optimal design of WDSs to minimize life-cycle costs and GHG emissions. The use of time-dependent emissions factors did not affect the trade-off between costs and GHG emissions, however, they were useful in identifying electricity usage with high emissions intensity. The selected discount factor is another important factor that affects the trade-off between cost and GHG emissions (Wu et al. 2010a), however, this is not applicable to studies of operations only. Stokes et al. (2014) discussed the cost-GHG nexus for WDSs, including energy generating infrastructure, and highlight the importance of using time-dependent emission factors and considering external factors that influence GHG emissions such as carbon taxes and discounting.

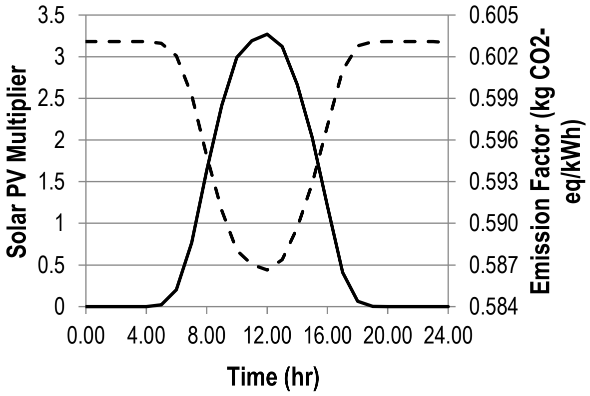


Figure 2.5: Daily variation in solar photovoltaic output (solid) and emission factors (dashed) (note that this figure has been taken from Blinco et al. (2016))

For systems that utilize alternative water sources in order to reduce reliance on potable supply, the volume of water harvested or produced by a system is also a key objective. Eusuff and Lansey (2004) considered the amount of water reclaimed from a recycled wastewater ASR system as a sole objective. The decision variables were the amount of recharge into the aquifer through a spreading basin (water infiltrates into the aquifer naturally) and the rate of extraction through pumping. Various targets for water quality, extraction well water level and residence time were analysed as constraints, with stricter targets resulting in less water extracted. McArdle et al. (2011) performed a multi-objective optimization of a stormwater harvesting system for potable use, considering three objectives; minimizing the present worth of capital and operating costs (as the cost per kilolitre of water delivered to the consumer), maximizing the average daily yield of potable water from the system, and minimizing the size of the storage in a public park to minimize the impact on the park's amenity. Decision variables were the capacities of the retention basin, storage reservoir, pump, and treatment plant, and the diameter of a transfer pipe, with no operational variables included. Without the third objective, optimal solutions would have utilized a very large reservoir in the public park, however, to minimize the size of this reservoir, the capacity of the treatment plant can be increased to obtain a similar yield. The cost of producing potable water from the harvested stormwater was greater than the cost of mains water, however, this cost may increase in the future with population growth and water security concerns. Karamouz et al. (2007) optimized an integrated surface and groundwater system for three objectives; maximising supply for irrigation demands, minimizing pumping costs and minimizing groundwater level fluctuations. If the groundwater level objective is ignored, water is taken from surface sources as a priority because of the high cost of groundwater pumping. Utilizing more groundwater, however, can help to regulate the groundwater level, which may be important in some systems. An alternative problem formulation is minimizing the amount of potable water used, such as in Mariano-Romaro et al. (2007) for industrial wastewater re-use.

2.4 Knowledge Gaps

The review of literature revealed gaps in the current knowledge that will be addressed in this thesis. With regard to pumping operations, complex operating rules such as those utilising variable trigger levels or combined trigger levels and scheduling have not been extensively analysed previously. The new EPANET2 capability for optimization of rule-based controls allows these more complex control types to be considered in optimization problems. This gap is addressed by **Objective 2** (Section 1.2) and **Chapter 4 (Publication 1)**, which optimises both simple and complex pump operating controls for two case study systems. Another gap is the consideration of GHG emissions, which has previously been considered using energy as a surrogate, or only with design decision variables, rather than operational decision variables. This is covered by **Objective 6** and also in **Chapter 4**, which specifically optimises GHG emissions and energy use separately for pump operations.

Previous analysis and optimization of alternative water source systems has been generally focussed on specific systems, with broad frameworks and methodologies not considered. **Objective 1** covers the development of a framework to optimize alternative water source systems and this is presented in **Chapter 5 (Publication 2)**. Application of this framework to two case studies – a harvested stormwater system and an integrated alternative water source supply system – is also included in **Chapter 5**. Optimization of detailed pump operations and consideration of hydraulics has often been left out of studies on alternative water sources. This gap is addressed in **Objective 3** and **Chapter 6 (Publication 3)**, which focuses on the harvested stormwater case study and utilises EPANET2 for detailed pump energy use and hydraulic calculations.

Many studies also perform only optimization, without in depth simulation or sensitivity analysis performed prior to carrying out the optimization study. Pre-optimization analysis by extensive simulation analysis can provide vital information for the formulation of the optimization problem. The size of the optimization problem can be reduced by identifying infeasible or undesirable options by simulation of the system. Sensitivity analysis can also be combined with optimisation in order to assess the robustness of the system to different conditions. This gap is addressed by **Objectives 4 and 5**, as well as in **Chapter 5** which performs a simulation analysis of a harvested stormwater system and in **Chapter 6** which then covers sensitivity analysis and optimization of the same system.

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Chapter 3 Synopsis of Publications

This chapter discusses the contributions made by the three publications presented in this thesis, their connections, and how they address the objectives of the work. The overall aim of this research is to develop and apply methodologies for optimizing complex pumping operations to systems that use alternative water sources. EPANET2 hydraulic simulation software is utilised in all of the publications, and this guarantees the conservation of energy and mass, which are constraints of the pump operations optimization problem. Figure 3.1 shows the contributions of the publications to the six specific objectives listed in Section 1.2. Publication 1 investigated five different types of pumping regimes using EPANET2 rule-based controls (**Objective 2**). These regimes were optimized and compared for two potable case study networks, considering objectives of minimizing pump energy costs and minimizing GHG emissions from pumping (**Objective 6**). Publication 2 presents a framework for the optimization of water supply and distribution systems that use alternative water sources (**Objective 1**). Sensitivity analysis of variables that have some uncertainty is also discussed (**Objective 5**) and two case studies demonstrate the application of the framework. Finally, Publication 3 applies the framework methodology from Publication 2 and the use of rule-based controls from Publication 1 to a harvested stormwater system (**Objective 3**). It includes extensive analysis of the case study system (**Objective 4**) and sensitivity analysis of the operation of the system to pump and tank sizing (**Objective 5**).

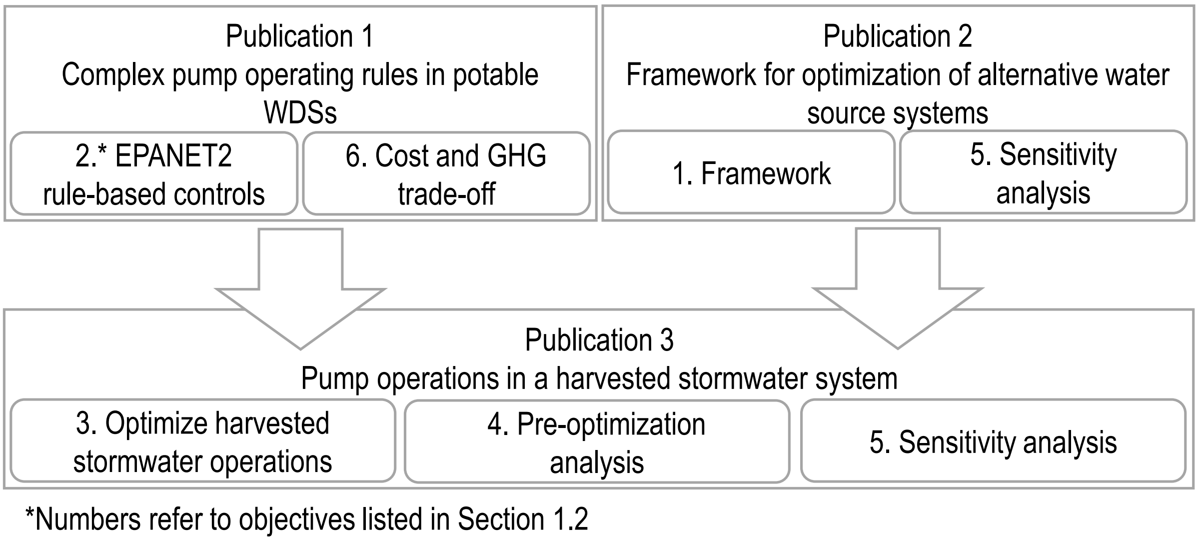


Figure 3.1: Connection between publications and their contributions to the research objectives

Optimization techniques have been extensively applied to pump operations problem for WDSs, both using trigger levels and scheduling. Previously, the ability to optimize complex operating rules using hydraulic simulation software was limited; simple trigger levels or scheduled could be controlled, however, trigger levels that vary with time could not. New developments for EPANET software to optimize the more complex rule-based controls were presented and tested in Marchi et al. (2016b). The main objectives considered in many optimization studies has been cost of energy use, system efficiency and reliability. Often, design and operation of a system have been optimized together, and in some of these cases, GHG emissions have been considered as an objective. GHG emissions are becoming a more important objective, as many water system managers have sustainability goals to consider. For existing systems, the majority of GHG emissions come from electrical energy use for pumping operations. Many previous studies focussing on GHG emissions have considered design decision variables rather than operational changes. Reducing the GHG emissions of existing systems through operational decision variables has not been extensively researched.

Publication 1 compares different operational pumping strategies, using both simple controls and complex controls, for cost and GHG emissions of pumping operations in potable WDSs. The new EPANET programmer's toolkit to alter rule-based controls was applied to consider five different types of pump operating regimes; (1) lower and upper trigger levels; (2) a reduced upper trigger level; (3) combined trigger levels and scheduling; (4) variable trigger levels; and (5) variable speed pump scheduling (Objective 2). A single-objective genetic algorithm as used to optimize the cost and GHG emissions from pumping separately (Objective 5). Costs were calculated based on the energy use of the pumps across a 24-hour period with a peak and off-peak electricity tariff. Energy use of the pumps was converted to GHG emissions based on emissions factors of energy generation technology (in kg of CO_2 equivalent per kWh). The emissions factors were based on the current South Australia energy generation breakdown, with some variation over the 24-hour simulation period based on the varying contribution of solar photovoltaic energy over a day. Two case study WDSs were used to compare the performance of the different pump operating regimes; a hypothetical one-pipe network, and a portion of the real-life South Australian WDS. Time-based scheduling operating strategies were found to perform better than the other regimes for both case studies. Significant cost savings were achieved for the South Australian system compared to its current operation.

Applying the methodologies that have been developed for and used on potable WDSs to alternative water source systems requires additional complexities to be taken into account. Traditional natural catchment supplies have often been split between hydrological analysis of the supply side, and hydraulic analysis of the demand side, with large storages delineating the two. Analysis and optimization of WDSs has assumed that there is always enough water available in the supply reservoir or there is a set discharge available from a water treatment plant. For alternative water source systems, this is not always the case, and it is important to analyse the supply from the catchment for sources such as stormwater and groundwater to know when the alternative water can be supplied, and when potable back-up should be used. Alternative water source systems also use infrastructure and technology that are not often part of a potable WDS and need to be modelled. This includes components such as wetlands bioretention basins in stormwater systems, bores in groundwater systems and small-scale treatment technologies in decentralized systems. Previous methodologies and frameworks for traditional potable WDSs therefore do not have the modelling capability required by alternative water source systems. Those developed for alternative water source systems, however, are often not generalized to many different water source types, and do not include detailed consideration of pumping and hydraulics.

Publication 2 presents a framework for the optimization of water supply and distribution systems that use alternative water sources along with a detailed discussion of the components and key variables (Objective 1). The options component describes the potential decision variables, both design and operational; the infrastructure component describes the physical components of the system to be modelled, including energy infrastructure that affects the evaluation of electricity costs and emissions; the analysis component describes the simulation of each potential system configuration and how it is evaluated against objectives and constraints; there is also a government policy component that covers policies from regulating bodies that may affect other parts of the framework. These all exist within an optimization algorithm structure, which would analyse and evaluate different potential solutions to find those that meet the constraints and perform best in terms of the objectives. Sensitivity analysis of demand, rainfall and streamflow, electricity and GHG emissions, discount rates, and climate change is also discussed (Objective 5). Two case study systems are used to illustrate how the framework can be applied to minimize the cost of water system operations. The first – the Ridge Park Managed Aquifer Recharge System – is a harvested stormwater and managed aquifer recharge (MAR) that supplies non-potable water for irrigation of public reserves. This system can be split into seasonal operations; winter stormwater harvesting and injection, and summer extraction and irrigation. The current operation of this system is analysed by hydraulic simulation in order to formulate an optimization of pumping operations. The second case study – the Orange Integrated Supply System – utilizes several different water sources; natural catchment, harvested stormwater, groundwater and imported water (from an adjacent catchment) to supply potable water to over 35, 000 people. In this system, it is important not to waste water by pumping from one of the three alternative sources only to have rain fill the natural catchment reservoirs, and this is considered by including an objective to minimize spills. Optimization of pumping operations for this case study focusses on reducing pump energy use. Figure 3.2 and Figure 3.3 demonstrate how these case studies fit in to the developed framework. The elements highlighted in the framework diagrams are those that are considered by each case study. Note that while optimization of the Ridge Park Case Study is not performed in Publication 2, it is covered in Publication 3 and therefore is highlighted in Figure 3.2.

As for potable WDSs, pumping energy is a large contributor to costs in alternative water sources systems, including harvested stormwater schemes. The focus of optimization of stormwater systems has been on their design, rather than operation. Harvested stormwater schemes often include multiple pumps between multiple storages, which can result in complex operating rules. The status of each pump relies on the level in more than one storage, and the level in each storage relies on the status of more than one pump. Optimization of complex pump operating rules, as in Publication 1, can be applied to harvested stormwater systems, however, additional modelling capability needs to be incorporated and different constraints and objectives considered, as discussed in Publication 2. Expanding current methods for optimizing pump operations in potable WDS to alternative water source systems will allow these systems to perform better and become more a desirable option to water system managers. As climate change and population growth raise water security concerns into the future, alternative water sources will become more necessary, and as such reducing their cost of operation is important.

Publication 3 explores the operation of a harvested stormwater case study system from South Australia both through simulation sensitivity analysis (Objective 5) and multi-objective optimization. The system has distinct winter and summer operational seasons; harvesting water from an urban creek, treating and injecting it into an aquifer during winter, and extracting water from the aquifer for irrigation of public reserves during summer (Objective 3). Most of the irrigation sites are on a gravity fed line, with the three closest to the harvest site, and highest in elevation, are on a pressure line. There are four pumps in the system, two used only in winter, one used in both winter and summer, and one used only in summer (Objective 3). Significant analysis of the system was preformed prior to optimization, to determine the current operation with different possible inflows, and determine the most appropriate way to model some of the components (Objective 4). For the winter operation, storage trigger levels were implemented as rule-based controls in EPANET and optimized to minimise the cost of pumping and maximise the volume of water harvested. During summer, irrigation scheduling, and the trigger levels for the bore extraction pump were optimized to minimize pumping costs. Restrictions on the aquifer injection rate and pressure are considered, as well as pressure and demand requirements at the various parks and reserves. The installation of new pumps and a larger tank are considered in both the simulation sensitivity analysis and optimization. Recommendations from the results of the optimization were to install new pumps with lower flow rates and better efficiencies, to utilize the full height of the storages by using wider trigger levels and to irrigate all reserves on the pressure line together.

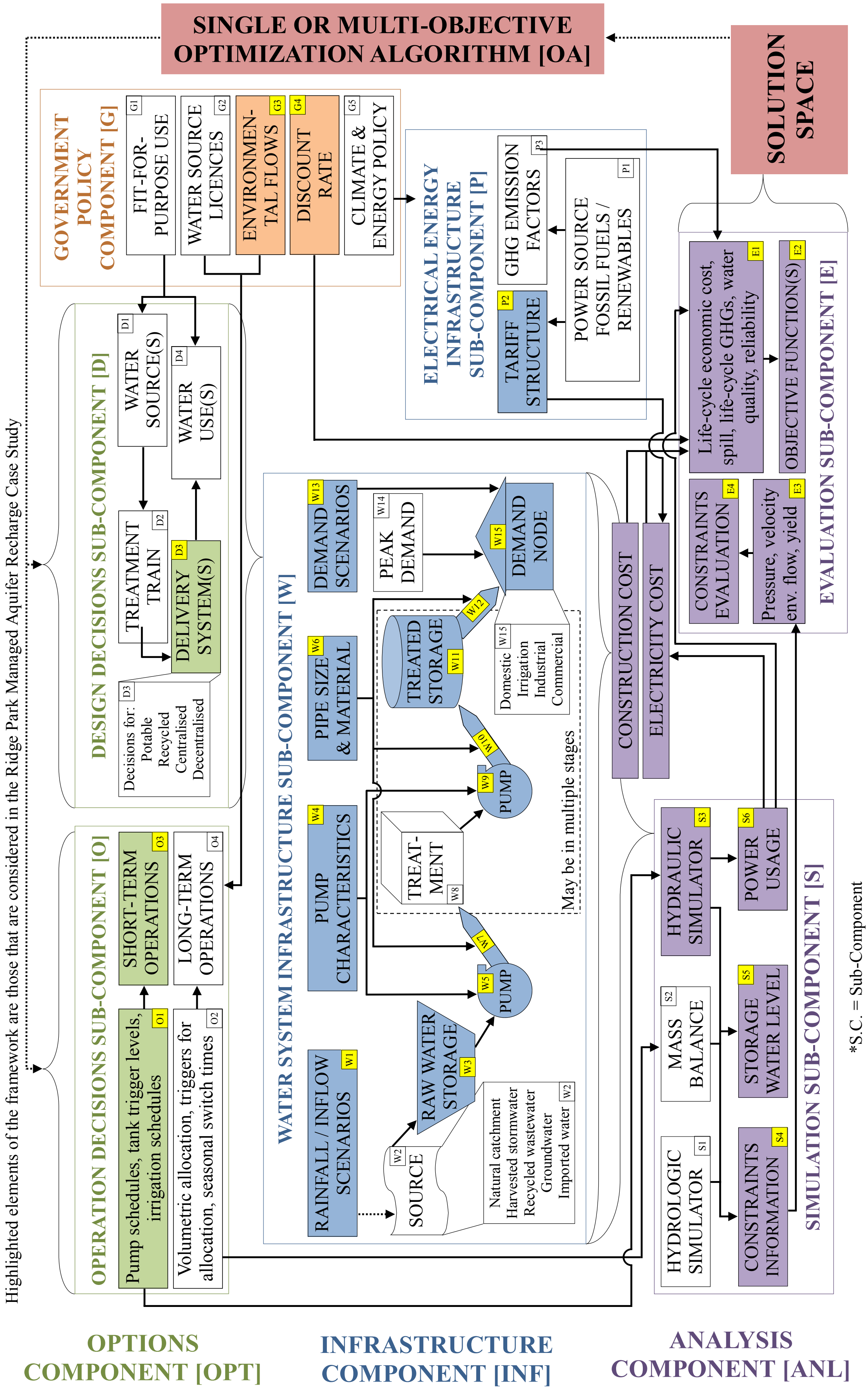
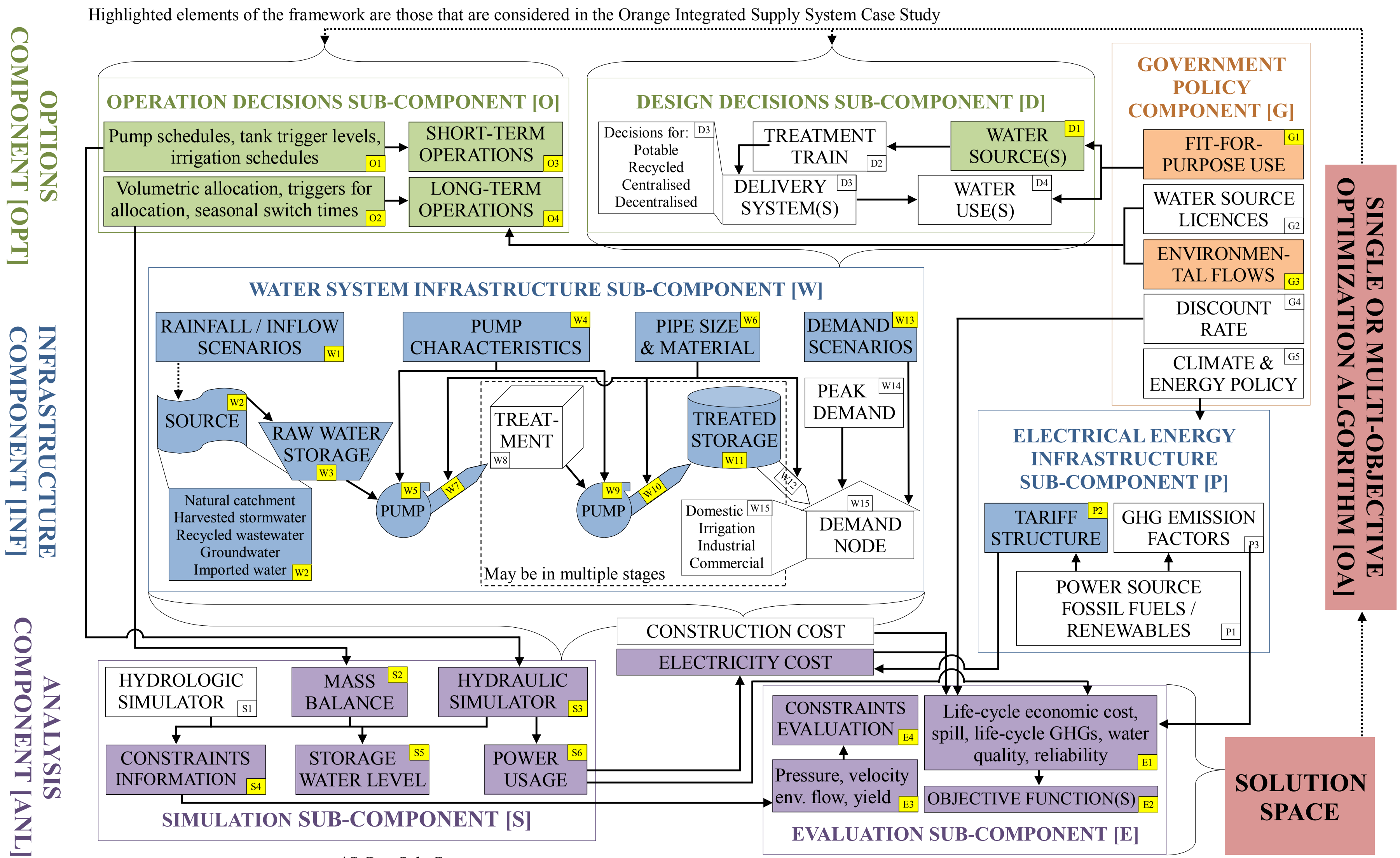


Figure 3.2: Elements of the framework presented in Publication 2 that are considered in the Ridge Park Managed Aquifer Recharge Case Study



*S.C. = Sub-Component

Figure 3.3: Elements of the framework presented in Publication 2 that are considered in the Orange Integrated Supply System Case Study

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Chapter 4 Comparison of Pumping Regimes for Water Distribution Systems to Minimize Cost and Greenhouse Gases

Publication 1

Blinco, L.J., Simpson, A.R., Lambert, M.F., and Marchi, A.

School of Civil, Environmental and Mining Engineering

The University of Adelaide, Adelaide, SA 5005 Australia

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Although the manuscript has been reformatted in accordance with University guidelines, sections have been renumbered for inclusion within this thesis, and details of references have been updated where applicable, the paper is otherwise presented herein as published (with permission from ASCE).

Primary Author	Blinco, L.J. (Candidate)
Contribution	Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.
Overall Percentage	80%

This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper and I hereby cerfity that the statement of contribution is accurate.

Signed:........ .... Date:......9/11/17...

Co-Authors

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate to include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Co-Author	Simpson, A.R.
Contribution	Research supervision and manuscript evaluation.

Signed:.. .... Date:...9/11/2017...............

Co-Author	Lambert, M.F.
Contribution	Research supervision and manuscript evaluation.

Signed:. .... Date:...9/11/17...............

Co-Author	Marchi, A.
Contribution	Research supervision and manuscript evaluation.

Signed:... .... Date:...9/11/17...............

Abstract

A single-objective optimization model has been developed for water distribution system (WDS) pumping operations, considering five different types of pump operating regimes. These regimes use tank trigger levels, scheduling, and a combination of both to control pumps. A new toolkit development to alter rule-based controls in hydraulic simulation software has allowed more complex pump operating regimes than have previously been considered to be optimized. The performance of each of the regimes is compared with respect to two different objectives: cost and greenhouse gas (GHG) emissions, which were optimized separately to allow the comparison of regimes to be made more clearly. Two case study networks, including one that represents a segment of the South Australian WDS, illustrate the effectiveness of the model. Time-based scheduling operating strategies were found to perform better than the other types of pump operating regimes. Significant cost savings were achieved for the South Australian case study network compared with its current operation.

4.1 Introduction

Energy costs can account for up to 65% of a water utility's operating budget (Boulos et al. 2001), and as such optimizing the cost of energy used for pumping will have significant benefits. Previous investigations of optimal pump operating strategies have generally been restricted to either lower and upper tank trigger levels or scheduling. Consideration of more complex pump operating regimes, for example, using trigger levels that vary throughout the day or combining trigger levels and scheduling, has been restricted in part by simulation model capabilities. A modification of the existing EPANET2 toolkit (Rossman 2000) has been developed by Marchi et al. (2016b) in order to modify rule-base controls. This new toolkit is called "EPANET2-ETTAR" (EPANET2 Toolkit to Alter Rules) and allows more complex pump operating regimes to be optimized. Human-induced climate change presents a serious global risk and action to mitigate the impact by reducing greenhouse gas (GHG) emissions is important. Production of electrical energy for water distribution system (WDS) pumping operations is the biggest contributor to GHG emissions from the water industry (Stokes and Horvath 2006; Wu et al. 2013).

This paper describes the development of a single-objective genetic algorithm (GA) optimization model for WDS pump operations integrating EPANET2 (including EPANET2-ETTAR) and a Microsoft Excel interface. The performance of five different types of pump operating regimes, including trigger levels that vary throughout the day and combined trigger levels and scheduling, is compared with respect to either the minimization of cost or the minimization of GHG emissions. The model is applied to two different case studies, a hypothetical one-pipe network and a real-life network from South Australia. In the second case study, two different pump sizes are considered and the results compared.

4.2 Literature Review

Efficient operation of WDSs can be achieved in several ways. The first step is to optimize the design of pumps and infrastructure, then, for existing or designed systems, pump operating rules can be optimized. Other strategies include recovering energy that would otherwise be dissipated using mini-hydro systems (Carravetta et al. 2013b; Fecarotta et al. 2015), reducing leakage to reduce pump and water treatment energy requirements (Giustolisi et al. 2013) and pump maintenance or replacements. There are many different objectives that can be considered to achieve efficient WDS operation, with the most common being to minimize the cost of electrical energy use. GHG emissions, based on energy use, or simply energy use itself can be used as environmental impact objectives (Simpson 2009). Water quality can be addressed by minimizing water age, which can be obtained from EPANET2 (Stokes et al. 2012a); pump maintenance cost, represented by pump switches, could be formulated as an objective (López-Ibáñez et al. 2005) or as a constraint (Lansey and Awumah 1994); system effectiveness (Carravetta et al. 2013a), resilience (Prasad and Park 2003), and leak reduction (Giustolisi et al. 2015) can also be used as objectives to improve the performance of WDSs.

The research presented in this paper focuses on the optimization of pump operating rules and the comparison of different types of pump operating structures. The case studies investigated are existing systems, and therefore no design optimization is considered. Objectives of pumping electricity cost and GHG emissions are considered separately and the characteristics of the optimal operating strategies for the objectives are compared. Multiobjective optimization of cost and GHG emissions for WDSs has been extensively covered in Wu et al. (2010a, b, 2011, 2012a, b, 2013) and Stokes et al. (2012b, c, 2014). This research is different in that it considers the effect of the different pump operating regimes on each objective individually. WDSs are often required to perform under different conditions, including different demands (e.g., seasonal and daily variations), emergencies (such as fires), and failure scenarios (such as power outages or pipe breaks), all of which have some uncertainty associated with them. Goryashko and Nemisrovski (2014) use stochastic methods to find optimal operating strategies that are robust to different demand scenarios, while Basupi and Kapelan (2015) combine Monte Carlo analysis with GA optimization for the WDS design problem. Analysis of emergency conditions and system failure in optimization has been much more widely applied to the design problem (e.g., Morley et al. 2012) while, for pumping operations, the use of a constraint on the minimum tank level or an emergency reserve storage is usually used to guarantee a reliable service.

Optimization of pump operations is highly complex due to a large number of possible pump operating strategies, variable electricity price, and fluctuating consumer demands. Operational policies are also subject to several constraints, including acceptable levels of water in storage tanks, maximum pumped volumes, long-term tank level balancing, nodal pressure limits, and maximum pipe velocities. Previous studies have usually been restricted to using either trigger levels (Paschke et al. 2001; Stokes et al. 2012b) or scheduling (Mackle et al. 1995; Goryashko and Nemisrovski 2014) and have not considered more complex operations such as trigger levels that vary throughout the day or combinations of trigger levels and scheduling. Lower and upper trigger levels represent the tank levels at which the pump(s) will turn on or off, respectively (when pumping to a downstream tank). Pump scheduling involves a set of temporal rules indicating when pumps should be switched on or off during the day. Scheduling requires an accurate estimation or a forecast of the expected daily water demand. Kazantzis et al. (2002) combined the use of trigger levels and scheduling, however, the trigger levels were fixed, and only the scheduling variables optimized. In EPANET2 (Rossman 2000), only simple controls (used for trigger levels) and pump patterns (used for scheduling) can be altered through the programmer’s toolkit (which can be used to trial different potential solutions within, say, a genetic algorithm optimization framework), and rule-based controls that are required for more complex operating regimes cannot be changed via the current toolkit. EPANET2-ETTAR gives access to these rule-based controls, therefore allowing more complex pump operating regimes to be considered in the pumping optimization process.

When a peak and off-peak electricity tariff structure applies, operational costs will be minimized by reducing the amount of pumping in the peak electricity period and deferring this pumping to the off-peak period. Operational costs will also be reduced by reducing the static head and by increasing the efficiency of the operating point. Maximizing the amount of off-peak electricity pumping can generally be achieved when the tank water level is at its maximum at the beginning of the peak period and at its lowest allowable level at the end of the peak period (Mackle et al. 1995; Kazantzis et al. 2002). A future approach, primarily concerned with GHG emissions, may be to pump steadily throughout the day with a variable speed pump (VSP), or in response to demands rather than electricity prices, with reduced energy through the use of slower velocities leading to a smaller friction head loss (Simpson 2009).

To properly account for the GHG emissions of WDSs, the sources of electricity should be identified because each will have different GHG emissions per unit of energy produced (Dandy et al. 2006). An emission factor is used to convert energy use to GHG emissions, considering all types of GHGs and their global warming potential as an equivalent mass of CO_2 (CO_2-eq). Previous studies have used an average GHG emission factor value for the region, including Dandy et al. (2006) and Wu et al. (2010a, b). Stokes et al. (2012b) took into account time-varying emission factors in their optimization of water distribution system design and operation. This identified high emission intensity electricity use and helped to reduce operational GHG emissions. The objectives of cost and GHG emissions may be aligned if no variation in electricity tariffs or emission factors is considered. When variations in these factors are taken into account, times with lower electricity prices will not necessarily coincide with times of lower emission factors, so optimal solutions for the two objectives will be different.

GAs represent an efficient method for the optimization of nonlinear problems, particularly when applied to complex WDSs. These algorithms are a population-based optimization technique that use coded representations of solutions (Goldberg 1989). After generating a random initial population, the GA determines the fitness of each potential solution by simulating them and evaluating an objective function. In many optimization problems, the objective function is based on cost, but it can also be formulated for other objectives. All solutions then go through GA operators based on evolutionary principles—typically selection, crossover, and mutation–to produce the next generation of solutions (Goldberg 1994). This process is repeated to converge on optimal or near-optimal solutions. When applied to the optimization of WDSs, GAs have been found to perform significantly better than other optimization techniques in areas of final solution optimality and iterative efficiency and are still competitive with other optimization methods today (Simpson et al. 1994; Wang et al. 2015).

4.3 Methodology

4.3.1 Optimization Model Formulation

The aim of this research was to compare the performance of five different pump operating control cases and the characteristics of their optimal solutions. To achieve this aim, a single-objective optimization model was developed, linking a GA with EPANET2- ETTAR and a Microsoft Excel Interface. EPANET2-ETTAR was used to simulate the different potential solutions from the GA in order to provide information about their performance relative to the objective function and constraints. The interface allowed the optimization parameters, decision variables, choice tables, and other inputs to be changed and customized for different networks. A single-objective GA with tournament selection, a choice of one- or two-point crossover, and bitwise mutation was used. Trigger level cases, with a small number of decision variables, used one-point crossover with a crossover probability of 0.8, a mutation probability of 0.05, 200 generations, and a population size of 200. Scheduling cases, with a large number of decision variables, used two-point crossover with a crossover probability of 0.7, a mutation probability of 0.02, 400 generations, and a population size of 300.

Wherever possible, full enumeration of the search space was used in preference to the genetic algorithm optimization. Two different objective functions were considered separately: cost and GHG emissions. The value of each objective function was calculated in terms of units per volume of water pumped to remove any bias between solutions that pumped different volumes of water over the day. For the cost optimization, the objective function was dependent on the energy use, electricity tariff rates, and the volume of water pumped over the whole day as given by Eq. (4.1)

$$OC = \frac{\sum_i T_i \times E_i}{V} \tag{4.1}$$

where OC = operational cost (dollars/m^3); T_i = electricity tariff for each time step i (dollars/kWh); E_i = energy consumption for each time step i (kWh); and V = total volume pumped (m^3) during the time simulation period. EPANET2-ETTAR was utilized to determine energy use for each time period as well as the volume of water pumped. In this research, a two-part electricity tariff has been considered, however, the pattern for the electricity tariff could easily be altered to consider other, perhaps more complex, tariff structures, such as a multipart tariff (more than two periods). In addition, a monthly peak energy demand charge (that is, an additional charge for the maximum kilowatt usage) could also be included if desired. An electricity price pattern can be specified in EPANET2, as well as a demand charge variable, which may apply if there is a monthly peak energy demand charge. Electricity costs were based on a representative South Australian tariff; a peak electricity price of 22 c/kWh (c = cents) between 7 a.m. and 11 p.m., and an off-peak electricity price of 9 c=kWh from 11 p.m. to 7 a.m.

The objective function for GHG emissions was based on the distribution of emission factors throughout the day and the energy used in each time period as given by Eq. (4.2)

$$OGHG = \frac{\sum_i F_i \times E_i}{V} \tag{4.2}$$

where OGHG = operational GHG emissions (kgCO_2-eq/m^3); F_i = emissions factor at each time step i (kgCO_2-eq/kWh); and E_i = energy at each time step i (kWh), which ranged from 0 to 23 for hourly time increments. Emission factor data were collated from Dey and Lenzen (2000), Lenzen (2008), and Evans et al. (2010) in order to take into account the varying contributions to GHG emissions from different energy technologies. To calculate the overall emission factor, South Australia's current energy sources, mainly gas, brown coal, and wind (Australian Energy Market Operator 2011), have been used. The emission factors were also adjusted to account for the variation in output from solar photovoltaic systems throughout the day and this output was greatest during the middle of the day (Figure 4.1). The contribution of each energy source at every hour was adjusted depending on the solar photovoltaic multipliers to give a daily variation in emission factors, which were lowest in the middle of the day (Figure 4.1). Minimization of energy consumption was also available in the model and acted as a surrogate for optimization of cost or GHG emissions where no daily variation in electricity tariffs or emissions factors was present.

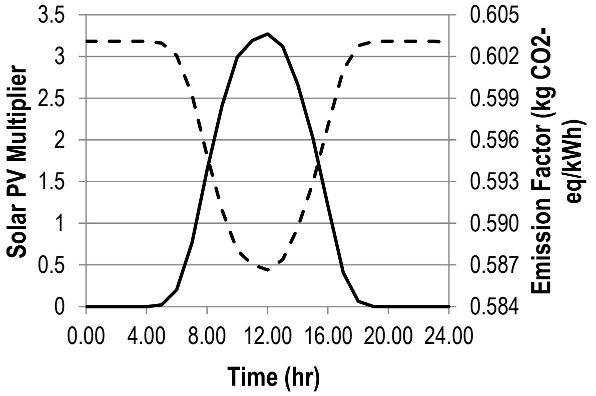

Figure 4.1: Daily variation in solar photovoltaic output (solid) and emission factors (dashed)

A number of constraints could be used in the optimization process, with penalties added to the objective function in the case of constraint violation. In addition to pressure, velocity, and head loss constraints, a minimum tank level may be specified to account for emergency and dead storages. There was also a tank balancing constraint, formulated as the maximum allowable difference between the storage tank's start and end level each day, and this could be used to prevent depletion of the water in the tank at the end of the simulation period. The maximum number of pump switches to occur within a 24-h period may also be specified, which could be used to address issues of pump maintenance costs.

4.3.2 Pump Operating Control Cases

Optimization of five distinct pump operating control cases was considered: (1) Case A, lower and upper trigger levels; (2) Case B, a reduced upper trigger level; (3) Case C, combined trigger levels and scheduling; (4) Case D, variable trigger levels; and (5) Case E, variable speed pump scheduling. The pump operation was optimized over a period of 24 h, with the simulation period beginning at the start of the off-peak tariff period and the water level in the tank being at its lowest allowable level. This serves as a known starting point for an optimal solution and also means that the final water level of the tank is likely to be close to the initial level as less pumping will benefit either of the objective functions. The available decision variables and constraints for each pumping control case are summarized in Table 4.1.

Table 4.1: Summary of decision variables and constraints for each control case

Case	Decision Variables	Constraints
A	Lower trigger level; upper trigger level	Minimum tank level Tank balancing tolerance Maximum pump switches Max./min. nodal pressures Max./min. pipe velocities Max./min. pipe headloss
B	Lower trigger level; reduced upper trigger level; upper trigger level	
C	Lower trigger level; upper trigger level; scheduled pump start(s); scheduled pump stop(s)	
D	Peak lower trigger level; peak upper trigger level; off-peak lower trigger level; off-peak upper trigger level	
E	Pump speed multiplier(s) (number depends on time interval)	

Control Case A optimized two decision variables—the lower and upper trigger levels in a downstream tank that determined when a pump would be switched on and off, respectively. While trigger levels are effective at keeping the water level in a tank within a certain operating range, there are both advantages and disadvantages to different trigger level operating strategies. Increasing either trigger level will increase the average static head of the system and therefore requires the pump to expend more energy to pump the same volume of water to the tank. A lower value of the upper trigger level may increase the amount of pumping required in the peak electricity tariff period because the tank will not be full at the start of this period, and hence may increase costs. The closer the trigger levels are to each other, the more times the pump will switch on and off during the day, which will increase general wear and tear of the pumps. Additionally, having both trigger levels or just the lower trigger level closer to the minimum allowable tank level may jeopardize the system’s capability to meet demand requirements. In times of extremely high demand, the rate at which the tank is draining may exceed the maximum pumping capacity, resulting in overall depletion of the tank volume even with the pump switched on. In these circumstances, if the trigger levels are too low, the water level in the tank may fall below the minimum allowable level.

A reduced upper trigger level was considered in Control Case B, which implemented EPANET2-ETTAR for optimization of rule-based controls. This model had three decision variables: a lower trigger level, an upper trigger level, and a reduced upper trigger level. During most of the 24-h simulation period, a reduced upper trigger level was permitted in order to reduce the static head of the system. There was a user-selected switch time before the start of the peak period at which the control would swap to the ultimate upper trigger level in order to fill the tank before the peak period.

Control Case C combined the use of tank trigger levels and pump scheduling. There were two trigger level decision variables—an upper and lower trigger level—which governed most of the pump operation. In addition to this, multiple time-based scheduling decision variables were also included that would specify a time for pump starts and pump stops. These time-based decision variables allow the tank water level criteria at the end of each tariff period [as identified by Mackle et al. (1995) and Kazantzis et al. (2002)] to be met where trigger levels alone cannot achieve this. For example, if the trigger levels in a particular network were such that the tank was draining at the end of the off-peak period, a scheduled pump start was added so that the tank is full at the start of the peak period. If the tank is filling at the end of the peak period, a scheduled pump stop was added to ensure the tank would be at its lowest allowable level at the end of the peak period and therefore avoid excess peak pumping.

Control Case D allowed for different trigger level sets for the peak and off-peak periods and this also utilized the EPANET2- ETTAR toolkit. There were four decision variables—an upper and lower trigger level in the peak period and an upper and lower trigger level in the off-peak period. In order to reduce the pumping cost, the two trigger levels used for the off-peak period will be higher than the two trigger levels used for the peak period because this allows the tank level to be closer to full at the beginning of the peak tariff period and close to the minimum allowable tank level at the beginning of the off-peak period. As suggested by Kazantzis et al. (2002), in order to optimize costs the tank should be at its minimum level at the end of the peak period and at its maximum level at the start of the peak period. The two different sets of trigger levels also allow for the reduction of the static head (and therefore energy use) during the period of higher electricity cost.

VSPs were incorporated into Control Case E, which optimized pump scheduling regimes. The decision variables in this model were the pump speed multipliers at each time interval. If fixed speed pumps (FSPs) were used, the only possible values for the pump speed multipliers would be 0 or 1. For VSPs, additional choices for the multipliers could range from 0.85–1.0 (as well as 0 for when the pump is off). The minimum pump speed multipliers calculated for the specific case studies take into account the guidelines by Marchi et al. (2012): (1) the minimum relative speed of the pump is larger than 0.7 so that the affinity laws can be used to predict the pump efficiency curve with reasonable accuracy, and (2) the shutoff head of the pump curve at the reduced speed is still higher than the static head of the system in order to deliver a flow larger than zero. In particular, the lower limit (0.85 in this case) depends on the pump shutoff head relative to the maximum system static head. Variable speed drive efficiency is not taken into account and this could affect the energy use of VSP solutions (Walski et al. 2003). When choosing a VSP for a particular system, the overall efficiency, including the variable speed drive efficiency and motor efficiency, should be taken into account. The time interval for the simulation of the pump schedule could be modified to reflect different demand patterns and pumping restrictions or requirements. For example, half-hourly time intervals would result in 48 decision variables, which could increase operational flexibility but also could increase optimization run times and effectiveness compared with hourly time intervals with only 24 decision variables. For systems with multiple pumps, a larger time interval may need to be used because otherwise the number of decision variables may easily become excessive, leading to long optimization run times and a larger search space, making finding the optimal solution more difficult.

4.4 Results

4.4.1 Case Study 1: One-Pipe Network

The models were initially used to analyze a one-pipe network introduced by Wu et al. (2010a), who performed a multiobjective optimization for the pump size and pipe diameter of the network, finding eight nondominated solutions in terms of capital and operating costs and GHG emissions. A design solution that represented an acceptable trade-off between costs and GHG emissions was used in this research (Figure 4.2 shows the network configuration). The network pumped water from an upstream reservoir to a downstream tank, which supplied an average peak day demand of 80 L/s. A diameter of 20 m was assumed for the downstream circular tank. Potential trigger level values for this network ranged from 1.0 to 5.0 m, with an increment of 0.2 m. The minimum possible trigger level value accounted for dead storage and emergency reserves. VSP multipliers considered were between 0.85 and 1.0 in 0.05 increments (Table 4.2). The minimum feasible VSP multiplier was determined using the first pump affinity law relationship between pump head (H_P) and speed (N) [Eq. (4.3)]. Pump speed can be reduced to a point where the shutoff head of the pump is equal to the static head of the system. At full speed [1,475 revolutions per minute (rpm)], the pump shutoff head is 143 m (H_{P1}) and the static head of the system when the tank is full is 100 m (H_{P2}). Applying Eq. (4.4) gives a minimum pump speed multiplier (N_2) of 0.84; to be conservative, a minimum value of 0.85 is considered (equivalent to approximately 1,254 rpm)

$$\frac{H_{P_1}}{H_{P_2}} = \left(\frac{N_1}{N_2}\right)^2 \tag{4.3}$$

$$\text{if } N_1 = 1 \text{ (full speed) then } N_2 = \sqrt{\frac{H_{P_2}}{H_{P_1}}} \tag{4.4}$$

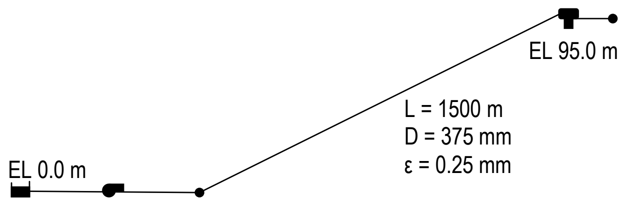

Figure 4.2: One-pipe network

<u>Control Case A</u>

Cost Minimization. When optimizing pump operating Control Case A, a lower trigger level of 1.0 m and an upper trigger level of 5.0 m was the best solution in terms of cost (Table 4.3). Because there were only two decision variables, each with 21 possible values (using increments of 0.2 m), the total number of possible solutions was $21^2 = 441$. Complete enumeration of the problem was performed and confirmed this result. The second-best through to the sixth-best solutions as presented in Table 4.3 show the same characteristic of having the trigger levels far apart, allowing maximum off-peak pumping. Solutions 7, 8, and 10 reduce energy use and therefore cost by reducing the static head of the system. These solutions all had a trigger level range of 1.6 m, with different lower and upper trigger levels. This trigger level range allowed the tank to half-fill twice during the off-peak period while also maintaining a lower water level than the first six solutions (Figure 4.3). As can be seen in the "Energy" column, the seventh solution had the lowest energy use per volume of water pumped from the cost optimization solutions. It had a greater cost per volume pumped because there is a greater percentage of energy being used in the peak period compared with the first six solutions ("Peak energy" and "Off-peak energy" columns). This indicates that for this network, the effect of the peak and off-peak tariff prices on the cost is greater than the effect of reducing the static head.

Table 4.2: Summary of choices and constraints applied to each case study

Decision Variable / Constraint	One-Pipe Network	South Australian Network
Trigger levels (m) (Cases A-D)	1.0-5.0 m, 0.2 m increment	4.0-7.9 m, 0.1 m increment
First pump start (Case C)	3am-7am, 5 min. increment	3am-7am, 5 min. increment
Second pump start (Case C)	4pm-10pm, 5 min. increment	-
Pump stop (Case C)	10pm-11:30pm, 5 min. increment	6pm-10pm, 5 min. increment
Pump speed multipliers (Case E)	0.85-1.0, 0.05 increment	0.88-1.0, 0.04 increment
Minimum tank level (m)	None, 0.8 m, 1.0 m	2.5 m, 4.0 m
Tank balancing tolerance (m)	None, 0.5 m	None, 0.1 m, 0.5 m
Maximum pump switches	12, 96	12, 96
Min./max. nodal pressures (m)	-	None, 20/120 m
Min./max. pipe velocities (m/s)	-	None, 0/5 m/s
Min./max. pipe headloss (m/km)	-	None, 0/50 m/km

The solutions represented in Table 4.3 and Figure 4.3 did not have a minimum tank level constraint enforced, which allowed the water level to fall significantly below the lower trigger level of 1 m due to high demands in the evening ("Minimum water level" column Table 4.3). If a minimum tank level constraint of 1 m is used, the optimal trigger levels are found to be 1.6 and 3.2 m (the 10th-best solution in Table 4.3), which has a minimum tank level of 1.32 m, well above the constraint. If the minimum level constraint is relaxed slightly, the optimal trigger levels are found to be 1.2 and 2.8 m (the eighth-best solution in Table

4.3). This results in a minimum tank level of 0.96 m, which may be acceptable to the decision maker. This shows the impact of the minimum tank level in finding the optimal trigger levels.

Table 4.3: Top solutions from pump operating Control Case A optimization for the one-pipe network

Solution	Cost ($/m³)	Lower Trigger Level (m)	Upper Trigger Level (m)	Trigger Level Range (m)	Energy (kWh/m³)	Peak Energy (%)	Off-peak Energy (%)	Min. Water Level (m)[a]	GHGs (kg CO_2-eq/m³)
Cost: 1st	0.0683	1.0	5.0	4.0	0.3725	72.0	28.0	0.36	0.2222
Cost: 2nd	0.0688	1.0	4.8	3.8	0.3721	73.1	26.9	0.40	0.2220
Cost: 3rd	0.0690	1.2	5.0	3.8	0.3728	73.1	26.9	0.59	0.2224
Cost: 4th	0.0695	1.0	4.6	3.6	0.3718	74.5	25.5	0.48	0.2219
Cost: 5th	0.0696	1.2	4.8	3.6	0.3725	74.4	25.6	0.66	0.2223
Cost: 6th	0.0697	1.4	5.0	3.6	0.3731	74.4	25.6	0.85	0.2227
Cost: 7th	0.0698	1.0	2.6	1.6	0.3702	75.9	24.1	0.77	0.2213
Cost: 8th	0.0699	1.2	2.8	1.6	0.3708	75.8	24.2	0.96	0.2218
Cost: 9th	0.0701	1.0	4.4	3.4	0.3716	75.9	24.1	0.60	0.2218
Cost: 10th	0.0701	1.6	3.2	1.6	0.3721	75.7	24.3	1.32	0.2225
GHG: 1st	0.0721	1.0	1.2	0.2	0.3685	81.2	18.8	0.45	0.2204

[a]Maximum water level for each solution is equal to the upper trigger level.

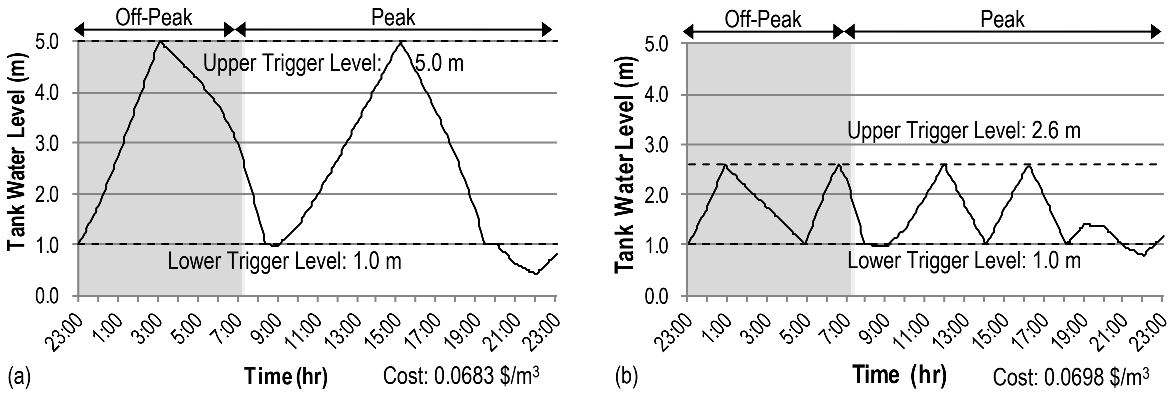

Figure 4.3: Daily tank level variation of the one-pipe network: cost optimization solutions: (a) pump operating Control Case A, first solution; (b) Control Case A, seventh solution

GHG Minimization. The optimal solution for GHG emissions was different than the optimal cost solution. The lower and upper trigger levels were as low and as close together as possible, at 1.0 and 1.2 m, respectively (while in the cost optimal solution they were as far apart as possible), reducing the static head. No effect due to the daily variation in GHG emission factors was observed in the optimal GHG solution. Because the trigger levels are very close together, the pump turns on and off quite often (62 pump switches) throughout the day, with the exception of two blocks in the peak period where the pump is on, resulting in higher costs. The seventh cost solution had lower GHG emissions than the other top 10 cost solutions ("GHGs" column of Table 4.3). Because it reduced energy use and costs by reducing the static head as well as reducing peak pumping, it was an acceptable compromise between the cost and GHG objectives.

Control Case B: Cost Minimization

With the addition of a reduced upper trigger level in Control Case B, the minimum operating cost was lowered to $0.0652/m³, compared with the $0.0683/m³ for the Control Case A solution. A switch time of 2 a.m. gave the lowest cost and was able to fill the tank just before the start of the peak period at 7 a.m. [Figure 4.4(a)]. Using a reduced upper trigger level did not benefit GHG emissions because there was no need to fill the tank before the start of the peak period and a reduced static head could be achieved using a low value for the upper trigger level.

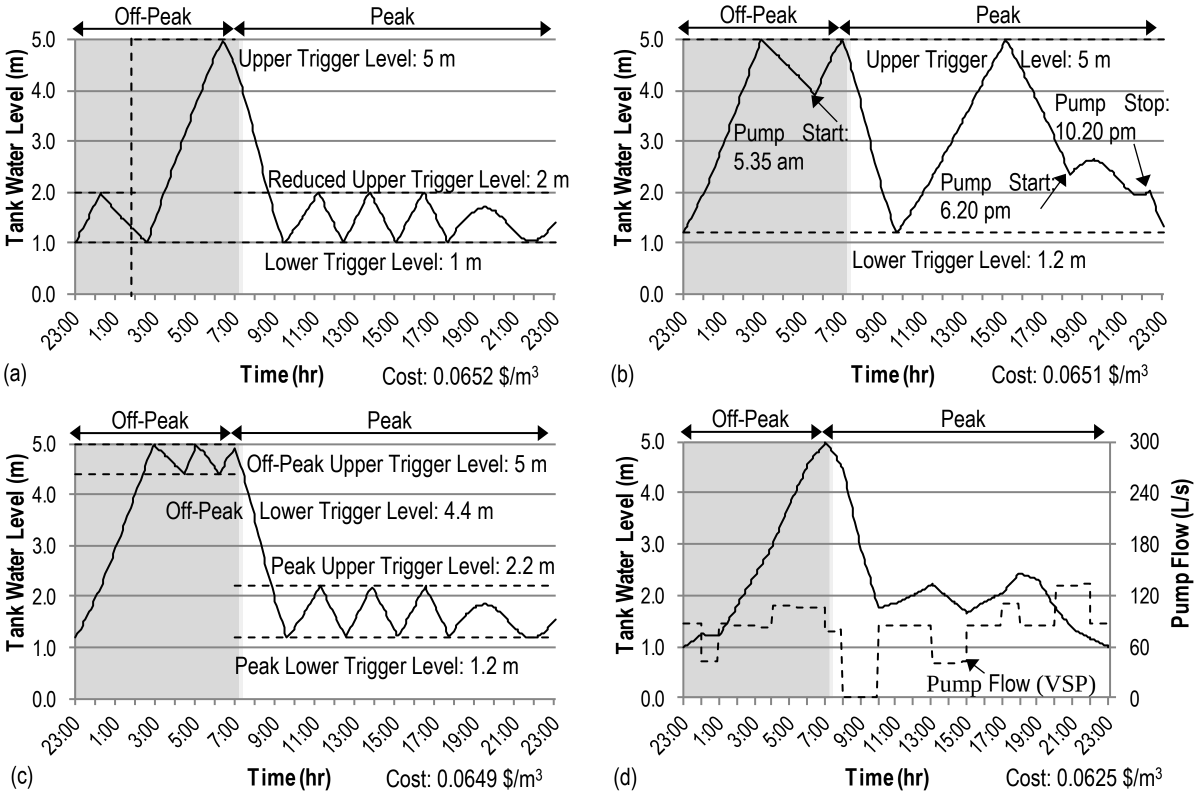

Figure 4.4: Daily tank level variation of the one-pipe network: cost optimal solutions for pump operating (a) Control Case B; (b) Control Case C; (c) Control Case D; (d) Control Case E

Control Case C: Cost Minimization

For Control Case C, the combination of trigger levels and scheduling, the cost was reduced slightly compared with the previous control cases at \$0.0651/m^3. Due to the high demands at the end of the peak period, shutting the pump down during this time would not be feasible. Therefore, an additional decision variable in the form of a pump startup during the peak time was considered as well as those proposed in the methodology. The time range for this pump startup was 4 to 10 p.m. at an increment of 5 min, which allowed the tank level to stay above 1 m, and a pump shutoff was considered between 10 and 11:30 p.m., also at an increment of 5 min. The optimal cost solution found using this strategy again had wide trigger levels of 1 and 5 m, the pump was started again at 5:35 a.m. and this allowed the tank to fill exactly for the start of the peak period [Figure 4.4(b)]. During the peak period, the optimal solution started the pump at 6:20 p.m. and then shut it down at 10:20 p.m. to have the tank empty at the end of the peak period.

Control Case D: Cost Minimization

Using variable trigger levels in Control Case D found an optimal solution that maintained a low water level during the peak period, with trigger levels of 1.2 and 2.2 m, and a high water level during the off-peak period, with trigger levels of 4.4 and 5.0 m [Figure 4.4(c)]. Even though this solution had a slightly greater percentage of pumping during the peak period compared with the Control Case C solution, it reduced the static head for much of the simulation period and was therefore slightly cheaper at \$0.0649/m^3.

Control Case E: Cost and GHG Minimization

Scheduling in Control Case E was able to find solutions with reduced cost and GHG emissions compared with the other control cases. The best cost solution using VSPs used lower pump speeds throughout the off-peak period to fill the tank exactly at the start of the peak period [Figure 4.4(d)] and had a cost of $0.0625/m^3. The use of FSPs was more expensive than VSPs; the cost optimal solution using FSP had a cost of $0.0656/m^3. FSP scheduling was less flexible than VSP operation and was not able to completely fill the tank for the start of the peak period. The optimal solution for GHG emissions pumped constantly throughout the day at reduced speeds, compared with the cost optimal solution, which pumped as much as possible in the off-peak period. This resulted in a cost of $0.0682/m^3 and GHG emissions of 0.2156 kgCO$_2$-eq/m^3, both of which are lower than for all of the solutions (cost or GHG optimal) presented in Table 4.3 for Control Case A.

4.4.2 Case Study 2: South Australian Network

The second case study was a real-life WDS in South Australia, consisting of 324 pipes, 278 nodes, two pumps (one on standby), one reservoir, and two tanks (Figure 4.5). This case study was chosen to show the advantages and disadvantages of the different pump operating control cases and objectives for a real network. With only one pump operating, the comparison between the control cases could be made clearly and their effect on the objectives more easily understood. With an average daily peak day demand of 30.7 L/s compared with the pump operational flow of 126 L/s, the pump in this network was oversized and only required to operate for 8 h each day. Under the current operational regime using trigger levels of 3.96 and 5.54 m, almost half of this pumping occurred during the peak electricity tariff period (Figure 4.6), when electricity rates were much higher (22 c/kWh compared with 9 c/kWh for off-peak). Cost and GHG emissions for the current operation were $0.0360/m^3 and 0.1460 kgCO$_2$-eq/m^3, respectively. The maximum tank water level was 7.92 m, with a minimum tank water level set at 2.5 m, representing 30% of the full volume to account for emergency reserves and dead storage. Trigger level values considered in the optimization ranged from 4.0 to 7.9 m at an increment of 0.1 m, with the initial tank water level set at 4.0 m for all simulations. The minimum pump speed multiplier was calculated to be 0.87 [Eq. (4.4) with a pump shutoff head of 92 m and maximum static head of 69.4 m], so choices for multipliers ranged from 0.88 to 1.0 in 0.04 increments (Table 4.2). The optimization results for all control cases for this network are presented in Tables 4.4 and 4.5 and discussed in the following sections.

Control Case A: Cost and GHG Minimization

For Control Case A, the optimal trigger levels to minimize cost for this network were 4.0 and 6.1 m, costing $0.0219/m^3, 39% less than the current operation (Table 4.4). The pumping in this solution occurred entirely within the off-peak period, with the tank filling between the hours of 11 p.m. and 6:30 a.m. and then draining for the rest of the day [Figure 4.7(a)]. Optimizing for GHG emissions found that trigger levels of 4.0 and 4.3 m reduced emissions to 0.1434 kgCO$_2$-eq/m^3, a 1.8% saving on the current operation (Table 4.4).

Control Cases B, C, and D: Cost Minimization

With all pumping able to be completed in the off-peak period, the addition of a reduced upper trigger (Control Case B) found optimal solutions with the same cost as the optimal trigger levels solution (Control Case A). Regardless of switch time, the optimal upper trigger level was greater than 6.1 m (the optimal upper trigger level value for Control Case A), and the reduced upper trigger level varied such that all the pumping could still be achieved during the off-peak period. This indicated that it was better to pump entirely within the off-peak period with the ultimate upper trigger level in effect rather than pump throughout the day with a reduced static head. Control Cases C and D, which also attempted to take advantage of the off-peak tariff and reduce the static head during the peak period, were also not useful (Table 4.4). In Control Case C, the optimal scheduled pump start occurred at times when the pump was already on and the optimal pump stop when the pump was already off, leaving the operation to be entirely governed by the trigger levels, which were the same as for Control Case A. In Control Case D, the operation was governed by the off-peak lower trigger level and the peak upper trigger level, which were the same as the Case A optimal trigger levels.

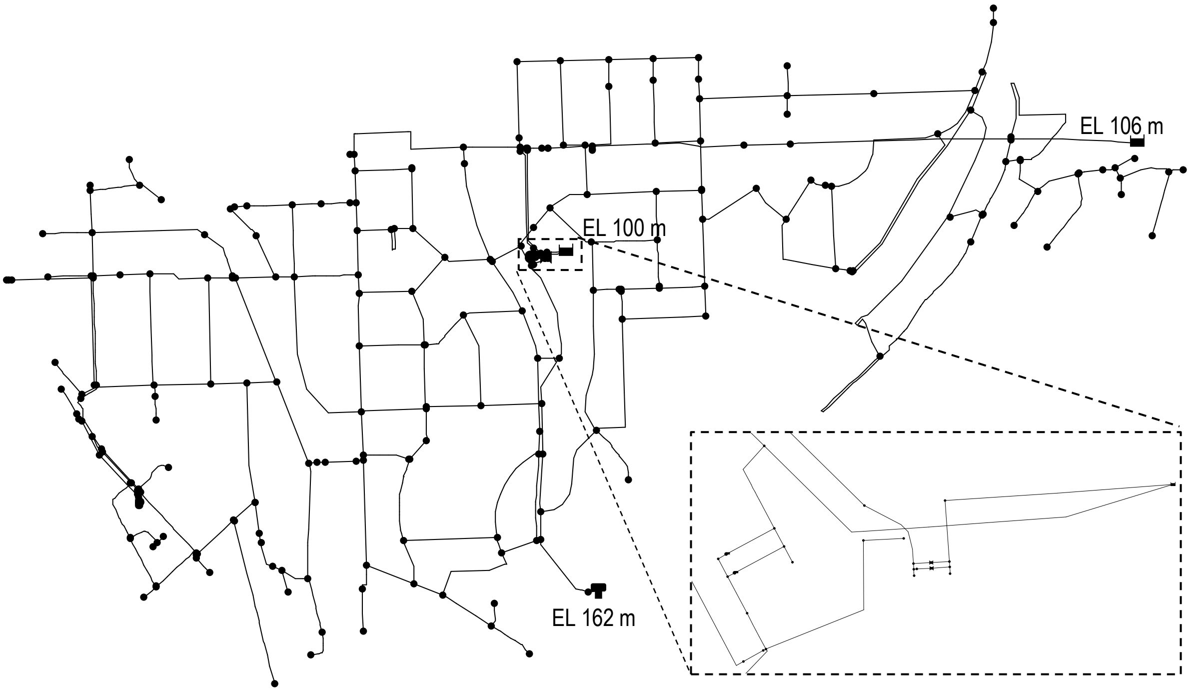

Figure 4.5: South Australian Network

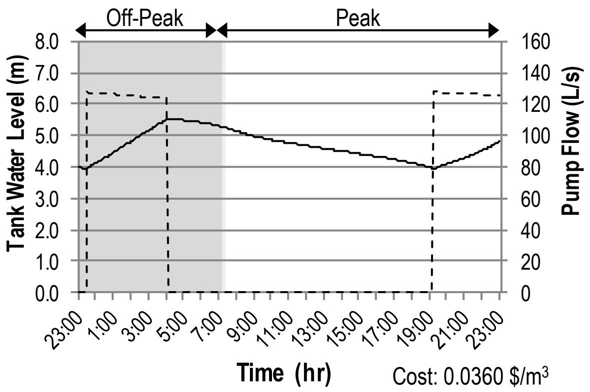

Figure 4.6: Daily tank level (solid) and pump flow (dashed) variation for the South Australian network: current operation

<u>Control Case E: Cost and GHG Minimization</u>

Optimization of VSP scheduling (Control Case E) found a marginally better solution to the cost optimal trigger levels operation with a cost of \$0.0218/m^3. It pumped at a reduced speed from 11 p.m. to 6 a.m. and then at full speed for the last hour of the off-peak period [Figure 4.7(c)]. While the reduced speed would lead to less friction loss through the system and hence reduced energy requirements, there was an extra 90 min of pumping that meant the cost and GHG emissions from the VSP solution were very similar to the trigger levels solution (Table 4.4). The optimal GHG solution pumped during half of the time periods, including during the middle of the day when the emissions factors were lowest. This solution had emissions of 0.1419 kgCO_2-eq/m^3, a reduction of 2.9% compared with current operation.

Table 4.4: Optimal solutions for each pump operating control case for the South Australian network

Control Case	Objective	Cost ($/m^3)	Cost Diff. (%)[a]	GHGs (kg CO_2-eq/m^3)	GHG Diff. (%)[a]	Peak Energy (%)	Off-Peak Energy (%)
A	Cost	0.0219	-39.2	0.1466	+0.4	0.0	100.0
A	GHGs	0.0438	+21.6	0.1434	-1.8	71.3	28.7
B	Cost	0.0219	-39.2	0.1464	+0.3	0.0	100.0
C	Cost	0.0219	-39.2	0.1466	+0.4	0.0	100.0
D	Cost	0.0219	-39.2	0.1466	+0.4	0.0	100.0
E	Cost	0.0218	-39.5	0.1459	-0.1	0.0	100.0
E	GHGs	0.0466	+29.3	0.1419	-2.9	80.4	19.6

[a]A negative difference indicates that the cost or GHGs in the optimal solution is less than the current operation (cost: $0.0360/m^3, GHG: 0.1460 kg CO_2-eq/m^3).

Table 4.5: Optimal solutions for each pump operating control case for the South Australian network with a smaller pump

Control Case	Objective	Cost ($/m^3)	Cost Diff. (%)[a]	GHGs (kg CO_2-eq/m^3)	GHG Diff. (%)[a]	Peak Energy (%)	Off-Peak Energy (%)
A	Cost	0.0291	-19.2	0.1339	-8.3	31.0	69.0
A	GHGs	0.0385	+7.0	0.1320	-9.6	64.7	35.3
B	Cost	0.0291	-19.3	0.1339	-8.3	31.0	69.0
C	Cost	0.0291	-19.2	0.1339	-8.3	31.0	69.0
D	Cost	0.0291	-19.3	0.1139	-8.3	31.0	69.0
E	Cost	0.0280	-22.3	0.1348	-7.7	27.0	73.0
E	GHGs	0.0409	+13.4	0.1315	-10.0	72.6	27.4

[a]A negative difference indicates that the cost or GHGs in the optimal solution is less than the current operation (cost: $0.0360/m^3, GHG: 0.1460 kg CO_2-eq/m^3).

Replacement with a Smaller Pump

In order to apply all of the pump operating control cases to a real-life network, the current pump was assumed to be replaced with a smaller pump that would be required to pump for more than the 8 off-peak hours each day. The current pump operated at a flow of 126 L/s at a head of approximately 70 m. Because the average demand was 30.7 L/s, a pump with a flow of approximately 40 L/s at a head of 70 m was selected. This pump required roughly 13 h of pumping per day. The shutoff head was 80 m, which gave a minimum pump speed multiplier of 0.93 and thus multipliers between 0.94 and 1.0 in increments of 0.02 were considered.

Control Case A: Cost and GHG Minimization with a Smaller Pump. Using the smaller pump in Control Case A, the optimal trigger levels for cost were 4 and 5.5 m; at $0.0291/m^3, this was more expensive than with the original pump (Table 4.5). This suggests that when there are large differences between the peak and off-peak cost of electricity, it may be more economical to install a larger, more expensive pump but have reduced operating costs by only pumping during the off-peak period. With a smaller pump, the tank did not fill as quickly and hence some of the pumping occurred during the peak period [Figure 4.7(b)]. This solution still reduced the cost by 19% compared with the cost of the current operation with the original pump (Table 4.5). Using the smaller pump reduced both GHG emissions and cost at the same time. The cost-optimal solution for Control Case A with the original pump slightly increased GHG emissions compared with the current operation. With the smaller pump, however, the cost-optimal trigger levels also reduced GHG emissions by approximately 8%. The optimal GHG trigger levels when the smaller pump was used were 4.0 and 4.7 m, further apart than with the original pump.

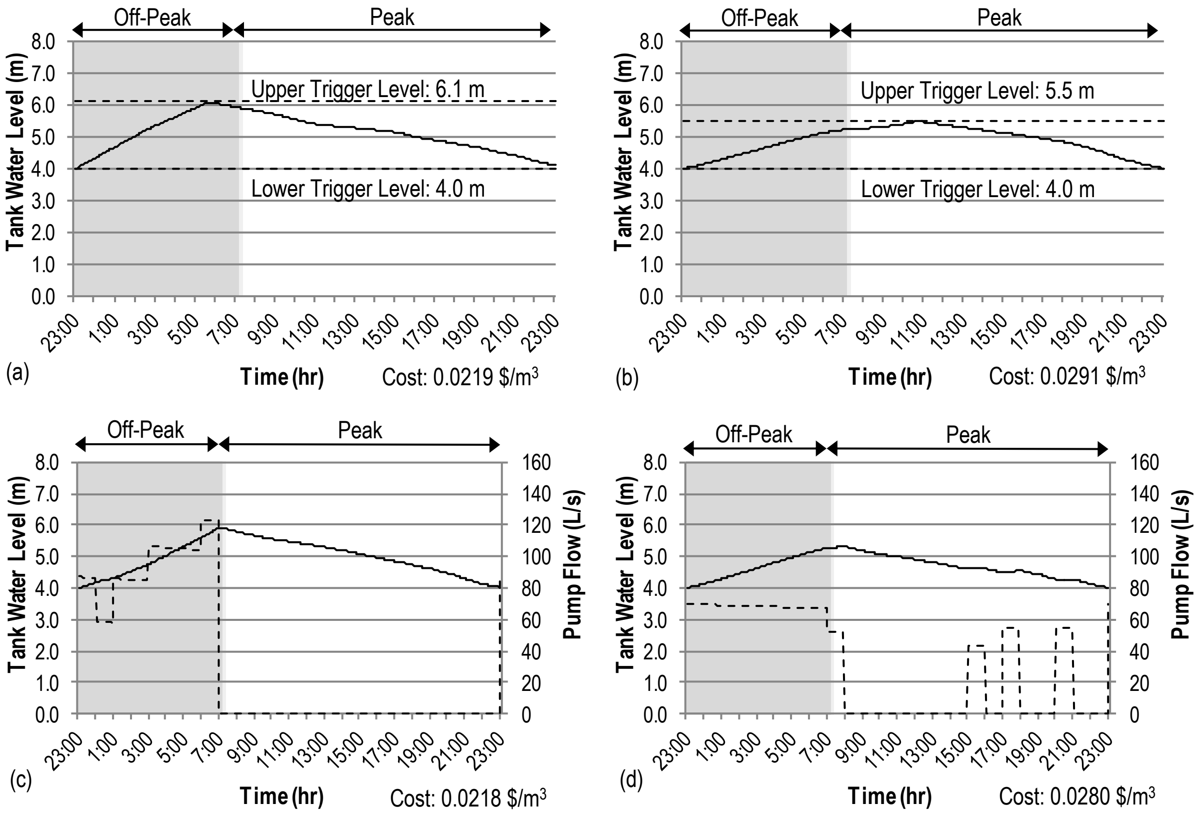

Figure 4.7: Daily tank level and pump flow variation for the South Australian network: cost optimal solutions for (a) Control Case A with original pump; (b) Control Case A with smaller pump; (c) Control Case E with original pump; (d) Control Case E with smaller pump

Control Cases B, C, and D: Cost Minimization with a Smaller Pump. With the use of the smaller pump, Control Cases B, C, and D found optimal solutions that had effectively the same operation as for the Control Case A solution (Table 4.5). With a reduced upper trigger level (Control Case B), the ultimate upper trigger level was ineffective and the pump was entirely controlled by the reduced upper trigger level at an optimal level of 5.5 m. When trigger levels and scheduling were combined (Control Case C), the same optimal trigger levels were found and the scheduled pump startup occurred when the pump was already on, and similarly the pump shut down when the pump was already off. With variable trigger levels (Control Case D), the peak levels governed the operation; during the off-peak period, the tank level did not reach the off-peak upper trigger level, and the peak upper trigger level, at 5.5 m, controlled when the pump stopped.

Control Case E: Cost and GHG Minimization with a Smaller Pump. VSP scheduling (Control Case E) with the smaller pump gave a better result than the trigger level operation with a cost of \$0.0280/m^3 (Table 4.5); however, it was still more expensive than with the original pump because some pumping in the peak period was required [Figure 4.7(d)]. The optimal GHG pump schedule with the smaller pump provided the best GHG solution for all of the South Australian network solutions in Tables 4.4 and 4.5 with emissions of 0.1315 kgCO_2-eq/m^3 giving a 10% saving on the current operation.

4.5 Conclusions

A single-objective genetic algorithm model has been developed to optimize pumping operations in water distribution systems. It was combined with a new toolkit for EPANET2 that allowed optimization of more complex pump operating strategies than have previously been considered to be performed. Five different pump operating control cases were implemented, using various types of trigger levels, scheduling, and the combination of both. Optimization of both cost and GHG emissions were considered separately in order to compare the optimal solution characteristics of the different pump operating control cases for each of these objectives. The optimization model was applied to two different case study systems, a hypothetical one-pipe system and a real-life system from South Australia.

VSP scheduling, implemented in Control Case E, performed better in terms of both cost and GHG emissions compared with the other control cases. Generally, solutions that had a lower percentage of energy used in the peak period were cheaper; the effect of the peak and off-peak tariff was greater than the effect of reducing the static head of the system. The more complex trigger level control cases (B, C, and D) were able to improve upon the cost of just using lower and upper trigger levels (Control Case A) because they were able to defer more pumping to the off-peak period. Cost and GHG objectives were not always aligned because of the variation in electricity prices and emission factors.

As well as producing optimal pump operating regimes, the optimization highlighted particular features of the two case study networks and their operation. For the one-pipe network, the optimization highlighted the high demands during the evening period, which necessitated the use of a minimum tank level constraint and affected the number of decision variables used in Control Case C. The oversized pump in the South Australian network made the use of Control Cases B, C, and D redundant because all pumping could be achieved in the off-peak period. Using a smaller pump was more expensive because some peak pumping was required; however, it was able to reduce GHG emissions at the same time as reducing cost compared with the current operation. The comparison of the two pumps suggested that when there is a large difference in peak and off-peak electricity prices, it may be more economical to spend more money initially with a larger pump, and be able to pump entirely within the off-peak period to reduce ongoing costs. The model proved effective, reducing costs by almost 40% compared with the current operation of the South Australian network.

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References

References are included in Chapter 8. In addition, the final published paper in Appendix B has the references listed.

Chapter 5 Framework for the Optimization of Operation and Design of Systems with Different Alternative Water Sources

Publication 2

Blinco, L.J., Lambert, M.F., Simpson, A.R., and Marchi, A.

School of Civil, Environmental and Mining Engineering

The University of Adelaide, Adelaide, SA 5005 Australia

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See Appendix B for a copy of the final published paper.

Statement of Authorship

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Although the manuscript has been reformatted in accordance with University guidelines, sections have been renumbered for inclusion within this thesis, and details of references have been updated where applicable, the paper is otherwise presented herein as published.

Primary Author	Blinco, L.J. (Candidate)
Contribution	Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.
Overall Percentage	80%

This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper and I hereby cerfity that the statement of contribution is accurate.

Signed:..... .... Date:......9/11/17......................................

Co-Authors

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate to include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Co-Author	Lambert, M.F.
Contribution	Research supervision and manuscript evaluation.

Signed:.. .... Date:....9/11/17..

Co-Author	Simpson, A.R.
Contribution	Research supervision and manuscript evaluation.

Signed:.. .... Date:.....9/11/2017.....................

Co-Author	Marchi, A.
Contribution	Research supervision and manuscript evaluation.

Signed:....... ...... Date:....9/11/17...................................

Abstract

Water security has become an increasing concern for many water system managers due to climate change and increased population. In order to improve the security of supply, alternative sources such as harvested stormwater, recycled wastewater and desalination are becoming more commonly used. This brings about the need for tools to analyze and optimize systems that use such sources, which are generally more complex than traditional water systems. Previous methodologies have been limited in their scope and cannot be applied to all types of water sources and systems. The framework presented in this paper has been developed for holistic analysis and optimization of water supply and distribution systems that use alternative water sources. It includes both design and operational decision variables, water and energy infrastructure, simulation of systems, analysis of constraints and objectives, as well as policies and regulations which may affect any of these factors. This framework will allow users to develop a comprehensive analysis and/or optimization of their water supply system, taking into account multiple types of water sources and consumers, the effect of their own design and operational decisions, and the impact of government policies and different energy supply options. Two case study systems illustrate the application of the framework; the first case study is a harvested stormwater system that is used to demonstrate the importance of simulation and analysis prior to optimization, the second utilizes four different water sources to increase security of supply and was optimized to reduce pump energy use.

5.1 Introduction

A changing climate and increasing population have put a strain on traditional water resources, which typically rely on natural catchment water. This has made water security an increasing concern for many water system managers, who have investigated options for reducing demand and supplementing supply. Alternative water sources, such as harvested stormwater, recycled wastewater and desalination, are increasingly being used to improve water security of cities and towns. Methods for simulation, analysis and optimization of traditional potable water distribution systems (WDSs) cannot necessarily be directly transferred to systems that use alternative water sources. Therefore there is a need to develop a methodology specifically for alternative water source systems, which includes both hydraulic and hydrologic considerations, as well as the many additional parameters and variables associated with alternative water sources. There are many modelling tools used in current practice for integrated water management, such as eWater Source, WEAP (Water Evaluation and Planning System) and Mike Basin. These modelling tools do not include hydraulic simulation, and therefore may not accurately represent performance of urban water networks. Moreover, this framework is not software, rather its purpose is to guide water system managers in how to best simulate and optimize their systems, particularly those that integrate multiple water sources, and natural and human-made systems. The framework should be used to determine which system components need to be modelled, which type of modelling tools are most appropriate, what regulations and policies need to be taken into account and how to evaluate the performance of the system.

The framework introduced in this paper can be applied to the optimization of the design and operation of water supply and distribution systems from source to consumer, considering multiple traditional and alternative sources, multiple uses and multiple objectives. Electrical energy sources and their effect on electricity prices and greenhouse gas (GHG) emissions are included, as are several types of government policies that may affect the design, operation, data and evaluation of the system. The objectives of this paper are to (1) develop a generalized framework that could be applied to any water supply and/or distribution system optimization problem and (2) outline the application of this framework to two case study systems with a focus on optimizing their operation.

5.2 Literature Review

Since 2000, there has been significant consideration of the concept of water security (Cook and Bakker, 2012) as water is increasingly seen as a fundamental and finite resource (Bogardi et al., 2012). Consequently, the use of alternative sources, such as harvested stormwater, desalination, recycled wastewater and rainwater, has gained traction (Fielding et al., 2015). Harvested stormwater schemes are often decentralized and used for non-potable supply such as household gardening and irrigation of public reserves (Naylor et al. 2012), however, in some cases are also used for potable supply (McArdle et al., 2011). While desalination is a climate independent (and therefore more reliable) source, is often not the most cost effective or environmentally sensitive option (Becker et al., 2010; Miller et al., 2015). Recycled wastewater is also climate independent, and generally used for large scale non-potable applications (Muga and Mihelcic, 2008; Oron et al., 2014), however, it can also be used for indirect or direct potable supply (Rodriguez et al. 2009; Nagal 2015). Domestic rainwater tanks are increasing in popularity and have benefits of reducing water usage from utilities and reducing stormwater runoff from houses (Campisano and Modic, 2012, Umapathi et al., 2013). Demand management strategies have also been used to reduce per capita consumption and therefore reduce the pressure on limited water supplies (Dawadi and Ahmad, 2013; Friedman et al., 2014).

Some alternative sources, such as harvested stormwater, introduce additional complexity to the problem of modeling and optimization than has been previously considered for traditional water systems (Marchi et al., 2016a). There is, for example, the need to consider the supply and distribution systems together, rather than separately, as it is less likely that there will be large storages isolating the supply side from the distribution side. When including the supply side, longer simulation times often need to be used, requiring rainfall and evaporation scenarios to be taken into account. The security of supply with regard to climate change needs to be considered (Paton et al., 2014; Cai et al., 2015), as some sources are climate dependent and some are climate independent. The social acceptability of using particular sources for particular applications and the willingness of consumers to pay more for alternative source systems to be constructed and maintained may need to be incorporated (Hwang et al., 2006; Londoño Cadavid and Ando, 2013; Fielding et al., 2015). The perception of risks associated with alternative water source systems by water system managers may also present a barrier to the implementation and success of such systems (Dobbie and Brown 2012; West et al. 2016). Many alternative sources also have associated externalities that result in either cost or benefit to the user, such as reduced effluent flow to the ocean or receiving water body by reusing wastewater and reduced urban stream flows by harvesting stormwater (Marchi et al., 2016a).

The increased use of alternative water sources then raises the question of how such systems should by analyzed and optimized to ensure they are implemented as effectively as possible. Stokes et al. (2014) developed a framework for optimizing the cost and GHG emissions of WDSs, taking into account both the design and operation of the system, energy sources and GHG emission factors. This study, however, was applicable only to traditional WDSs, with no consideration of the supply side and alternative water sources. Chung et al. (2008) developed a mathematical model for evaluating integrated water supply systems with decentralized treatments. Multiple sources, uses, transportation and treatment systems can be considered, however only surface water, groundwater and recycled wastewater sources are included. This model does not incorporate any optimization procedure, only analysis of different options developed by the user. Makropoulos et al. (2008), with further developments in Rozos and Makropoulos (2013), produced a decision-support tool for modeling the urban water system from source to tap. The software can be used to select combinations of water saving strategies and technologies, including how much water from each type of demand (for example domestic, commercial) is obtained from each source and how the system is operated. It uses a demand-oriented, water balance approach and does not include capability for other types of simulation models such as hydraulic and hydrologic modeling.

Uncertainty, particularly with regard to climate change, is an important consideration that has been taken into account in several methodologies. Paton et al. (2014) developed a framework for water supply system planning with alternative sources and climate change considerations, while Beh et al. (2014, 2015) developed two methods for optimal sequencing of urban water supply augmentation options under deep uncertainty regarding demands and climate. The research by both Paton et al. (2014) and Beh et al. (2014, 2015) considered only the planning of water supply projects, and did not optimize the specific design or operation of the systems. Sequencing is also considered in Cai et al. (2015), however, in this case it is applied to planning of drought mitigation strategies in agricultural systems. They consider multiple decision stages in which options such as infiltration ponds, parallel terraces, irrigation triggering threshold and irrigation water sources can be implemented. Marchi et al. (2016a) developed a methodology for optimizing the design of harvested stormwater systems taking into account future climate scenarios; however, it does not apply to other types of alternative sources or optimization of system operation. It does include a detailed analysis of the associated externalities, such as reduced peak flows and improved economic value of properties near stormwater schemes. Ashbolt et al. (2014) introduced a framework for planning of short-term operations for water systems using surface water, groundwater, desalination, and recycled wastewater with multiple objectives and multiple inflow replicates to account for uncertainty. Long-term operating strategies and the design of the system were not included and the operating strategies considered were limited to bulk water transfers and not the operation of pumps and smaller storages.

5.3 Framework for the Optimization of Alternative Water Sources

The framework presented in the current paper was developed to guide the modeling and optimization of water supply and distribution systems that use alternative water sources. It is comprised of several components and sub-components that fit within an optimization structure, for example, a multi-objective evolutionary algorithm (Figure 5.1). The options component [OPT] describes the potential 'decision variables' that are available in an optimization problem, that is, the factors that can be changed in order to produce a different outcome. This includes both the initial design of the water supply and distribution infrastructure and the long- and short-term rules that govern the operation of the system once it has been commissioned. The infrastructure component [INF] describes the physical components of the system that need to be modeled and the data associated with each, including both water infrastructure and energy infrastructure, which may affect the evaluation of electrical energy cost and life-cycle GHG emissions. There is also a government policy component [G] that covers the policies from regulating bodies that may affect other aspects of the framework. The analysis component [ANL] describes the simulation of each potential system configuration and evaluation against objectives and constraints. The optimization algorithm [OA] investigates different possible combinations of decision variables from the options component, models the system according to the infrastructure component and evaluates it using the analysis component to find the optimal solution(s).

Details of the components and sub-components are shown in Figure 5.1 and described in Sections 5.3.1 to 5.3.4. Table 5.1 summarizes the parameters that need to be considered in the optimization and simulation of alternative water source systems with respect to the different items that are presented in Figure 5.1 and in the following sections. There are three (non-exclusive) categories that each parameter may be placed in – decision variables, parameters that are set, and uncertain parameters. Decision variables are parameters that the user may be able to examine using optimization. It is important to note that in most optimization problems, not all of these parameters will be available as decision variables at once, and it is likely that only a small number will be considered. For example, when optimizing pump operations for an irrigation system, only the first three 'decision variables' shown in Table 5.1 (pump schedules, tank trigger levels, and demand scheduling) may be considered. The remaining parameters that are designated as decision variables in Table 5.1, particularly those relating to the design of the system (for example, delivery system layout and pump sizing) would already be set and not able to be optimized if the existing infrastructure cannot be modified. The parameters that are set are those that very rarely, if ever, are able to be optimized by the user. These include parameters that would be controlled by external sources, for example consumers of domestic or commercial demands, pipe manufacturers and higher level government and regulatory bodies; and also parameters that need to be predefined to a known or assumed value before optimization or simulation can be performed, for example, fire demand/reserve, hydrologic/hydraulic variables and objective and constraint selection and definition. The final category, uncertainty, designates those externally set or predefined variables that are not well known or may be subject to change in the future and therefore may need to be considered in a sensitivity analysis. While the selected values of decision variables have an impact on the performance of a system, they are generally within the control of the decision maker, and therefore are not classed as 'uncertain'. It is important to note that the categorization in this table is indented as an indication of how each parameter is typically treated. There are, of course, exceptions to this, as almost all of the parameters could be considered as decision variables if desired and have some associated uncertainty. For example, environmental flows have been designated as an externally set parameter, as it is likely that the operator of a system will have to meet requirements set by an external organization such as the Environmental Protection Agency. They may, however, want to investigate providing greater environmental flows, or show the benefits of reducing their environmental flow requirements and being able to supply more water elsewhere.

5.3.1 Options Component [OPT]

The options component covers the potential decision variables (and the range of possible choices for the decision variables) for an optimization problem. This component is split into two sub-components; the operational decisions sub-component [O] and the design decisions sub-component [D]. Design decisions include elements that can be changed before a system is constructed, such as the layout and capacities, materials and other properties of the various infrastructure components. Operational decisions include elements that can be changed after construction during the daily management of the system, such as the operating rules for pumps and valves and allocation of water from different sources.

<u>Operational Decisions Sub-Component [O]</u>

Both short- and long-term operations are considered in the operational decisions sub-component. The critical aspects of this sub-component (items in **bold** can be optimized), as shown in Figure 5.1 and Table 5.1 are:

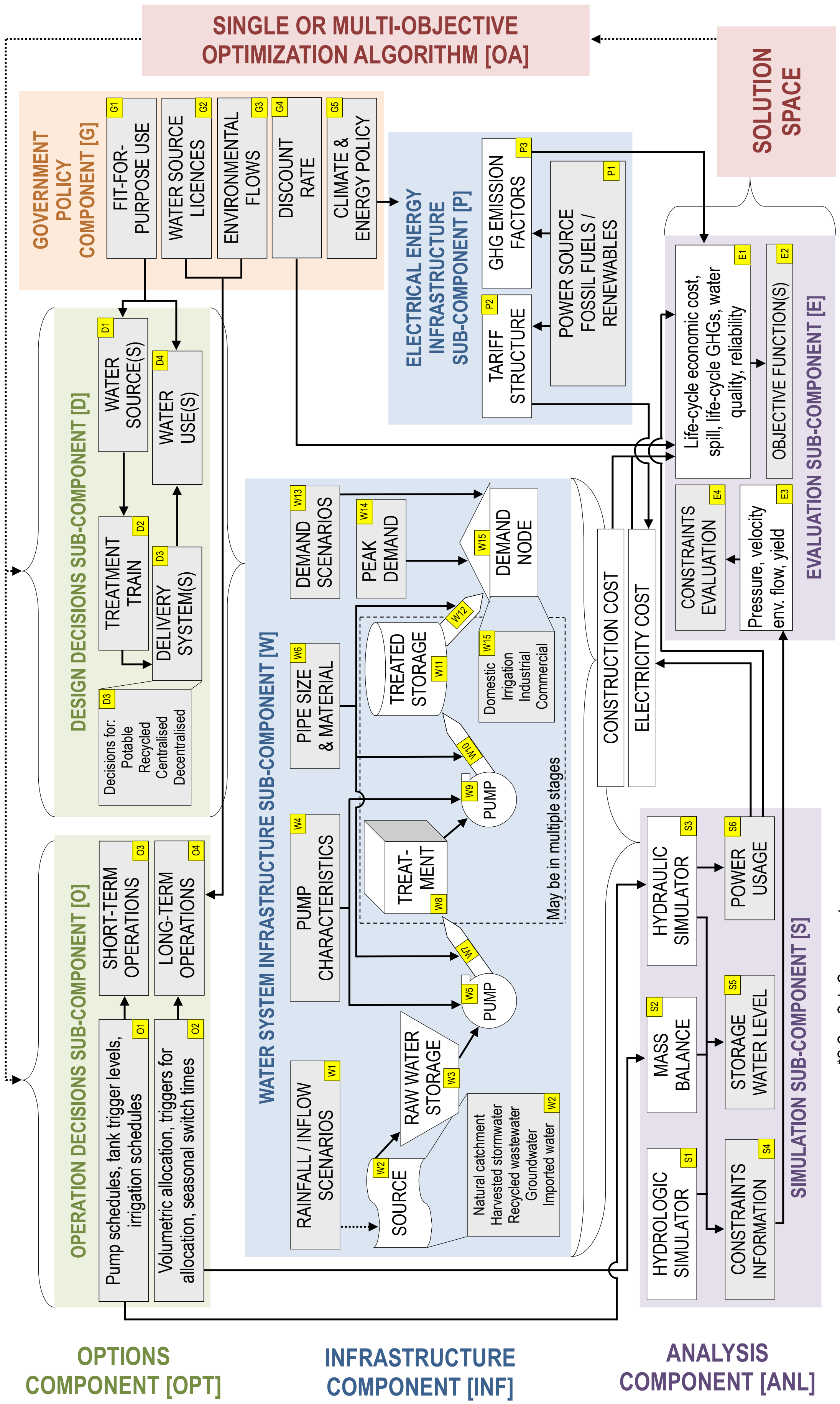
[O1] the specific short term operating strategies including **pump schedules** (when pumps are turned on or off based on time), **trigger levels** (water levels in tanks or other storages that determine when pumps or valves turn on or off), **irrigation or demand schedules** (for systems where they can be pre-determined), **valve settings and operating rules**, and **pressure settings for pumps** (to maintain the set pressure at a particular point).

[O2] the specific long term operating strategies including **volumetric allocation of water** from different alternative sources, **trigger levels** (for example in reservoirs) that determine allocations from different sources or water demand restriction levels, **switch times between different operating regimes** (for example between different trigger level sets for different seasons) and power source selection.

[O3] the overall short-term operating strategy, including operating rules that are optimized in [O1] and operating rules that are pre-set and are not to be optimized (acting as constraints). Where there are multiple operating rules, the priority of each rule and order they are enforced in is important to consider.

[O4] the overall long-term operating strategy, including operating rules that are optimized in [O2] and operating rules that are pre-set and are not to be optimized. Again, the priority and order of the rules is important to consider.

Most systems have multiple operating conditions to meet and therefore multiple operating rules will be in place. Prioritization of the different operating rules is important, and this may be set by the operator or be chosen by the optimization tool. This component requires information from the government policy sub-component ([G] in Figure 5.1), specifically in terms of water source licensing and environmental flow regulations. These policies would typically be regulated by local or state government departments or the environmental protection authority. Operational rules set in this sub-component will inform the simulation sub-component [S] as they will need to be represented in any simulation model(s) of the system.



*S.C. = Sub-Component

Figure 5.1: Schematic of the framework for optimizing the design and operation of alternative water source systems

Table 5.1: Summary of parameters for the design and operation of alternative water source systems

Parameter	Decision Variable*	Parameter that is set	Uncertain Parameter	Relevant Items in Figure 5.1
OPERATIONAL INPUTS [O]				
Pump schedule	X			O1
Tank trigger levels	X			O1
Tank / storage maximum and minimum allowable levels		X		O1, W3, W11
Demand pattern (irrigation, agriculture)	X			O1, D4, W13
Demand pattern (domestic, commercial, industrial)		X	X	O1, D4, W13
Demand flow rate (peak, average, peak day)		X	X	O1, D4, W14
Valve settings or operating rules	X			O1
Pump pressure settings	X			O1
Volumetric allocation of water	X			O2
Reservoir trigger levels	X			O2
Switch time between operating regimes	X			O2
Priority ranking of operating rules		X		O3, O4
DESIGN INPUTS [D] AND WATER INFRASTRUCTURE [W]				
Water source selection	X			D1, W2
Water source infrastructure (layout, capacity)	X			D1, W2
Treatment type selection	X			D2, W8
Treatment infrastructure (layout, capacity, treatment rate/level)	X			D2, W8
Delivery system type selection	X			D3
Delivery system layout (lengths, elevations, junctions, tank locations)	X			D3, W7, W10, W12, W15
Pipe material and diameters	X			D3, W7, W10, W12
Pipe parameters (unit cost, pipe wall roughness (ε), wall thickness, embodied energy)		X	X (ε)	D3, W6, W7, W10, W12
Pump sizing	X			D3, W5, W9
Pump performance characteristics and cost		X		D3, W4
Tank sizing (capacity, height, diameter)	X			D3, W3, W11
Fire demand / reserve		X		D3, W11
Water user type selection	X			D4
Rainfall / streamflow series		X	X	W1
Reservoir capacity and volume curve	X			W3
Pond (e.g. wetland) capacity and volume curve	X			W3
Prioritization rules for demands types		X		W15
OTHER INPUTS [P], [G] AND [S]				
Power source selection		X	X	P1, P3, G5
Electricity tariff structure and cost		X	X	P2
GHG emission factors		X	X	P3, G5
Fit-for-purpose requirements		X		G1
Water license amounts		X		G2
Environmental flow amounts		X		G3
Discount rate		X	X	G4
Hydrologic variables (e.g. permeability)		X		S1
Hydraulic variables (e.g. water temperature)		X		S3
OPTIMIZATION PROBLEM FORMULATION [E]				
Objective selection		X		E1
Objective function(s)		X		E2
Constraint selection		X		E3
Constraint limits (maximum and minimum)		X		E4
Penalty costs		X		E4

*Note: Parameters specified as decision variables are shown in bold throughout Sections 5.3.1 and 5.3.2.

<u>Design Decisions Sub-Component [D]</u>

This sub-component incorporates all of the design decisions that are available to the designer for the entire water supply and distribution system, from source to user. The critical aspects of this sub-component (items in **bold** can be optimized), as shown in Figure 5.1 and Table 5.1 are:

[D1] the **water sources selected** to be used including natural catchments, harvested stormwater, recycled wastewater, groundwater, imported water, domestic rainwater, desalination, domestic greywater and sewer mining; and the **layout and capacity of source infrastructure**.

[D2] the **types of treatment selected** including centralized treatment at plants such as mechanical filtration, chemical dosing, ultraviolet treatment and ozonation, and decentralized in situ treatments such as gross pollutant traps, wetlands and biofilters; and the **layout, capacity, dosing rates and retention times for treatment facilities**.

[D3] the **type and configuration of the delivery system** used including potable, non-potable (for example dual reticulation systems to deliver recycled water), centralized and decentralized, and the infrastructure design variables such as **system layout, pipe sizes, lengths and materials, pump sizing, valve sizing, and tank sizing**.

[D4] the **types of water users** that are supplied by the system including potable, irrigation, agriculture, industrial, non-potable domestic/commercial and firefighting, and the demand rate and pattern for water use (for example, scheduling of irrigation demands).

Regulations on fit-for-purpose water use from the government policy component [G] in Figure 5.1 inform what water sources can be used for particular applications and these are likely to be specified by state or federal government departments or health authorities. Generally, sources such as harvested stormwater and recycled wastewater cannot be used for potable supply and rather serve non-potable demands in dual-reticulation systems or are supplied to irrigation, agricultural and industrial users. There may be some systems, however, in which necessary approvals have been obtained to use these sources for potable supply. The design decisions are inputs to the water system infrastructure sub-component [W] which describes the system elements and data to be modeled.

5.3.2 Infrastructure Component [INF]

The purpose of this component is to describe the infrastructure that needs to be modeled in order to evaluate the objectives and constraints of the problem. There are two sub-components; the water system infrastructure sub-component [W] and the electrical energy infrastructure sub-component [P]. Water system infrastructure includes the specific aspects of the water supply and distribution system and the data required, including construction and maintenance costs. Electrical energy infrastructure includes the power source (fossil fuel types and renewable types) and the electricity price and GHG emission factor data needed.

<u>Water System Infrastructure Sub-Component [W]</u>

This sub-component includes the specific infrastructure aspects of the water system design and the relevant data that is needed in order to simulate it. Most systems and optimization problems will not require all of these factors to be considered or modeled; however, the purpose of this framework is to cover a large range of the possible requirements for an optimization and hence the scope is intentionally broad.

The water system infrastructure sub-component [W] as shown in Figure 5.1 represents a system with one water source, one treatment plant, one storage tank and one demand node. In reality, many systems will have more than one of each of these components, particularly the treated storage [W11] and demand node [W15]. Pumping of water between storages may occur in multiple stages, particularly when there is a large difference in elevation. For typical centralized potable WDSs, all treatment will occur at one water treatment plant. In decentralized systems such as for harvested stormwater schemes, however, treatment may occur in multiple stages. For example, a gross pollutant trap may be located on an urban creek before the water is collected in a harvest pond, then the water may be pumped to be treated through a wetland, and then treated again in a treatment plant.

The critical aspects of this sub-component (items in **bold** can be optimized) as shown in Figure 5.1 and Table 5.1 are:

- [W1] the rainfall or inflow scenarios for the water source; for example rainfall or streamflow scenarios for natural catchments and stormwater sources, or a sewer system flow pattern for recycled wastewater. Sources such as desalination and, depending on the temporal scale of the optimization, groundwater, do not usually require an inflow scenario. Rainfall and streamflow scenarios may be a data series obtained from measurements at gauging stations or modeled in a hydrologic simulation program [S1]. Multiple inflow scenarios may be used, particularly for systems with highly variable inflows. Losses such as evaporation and infiltration may also need to be taken into account for sources with large open storages such as reservoirs and natural water ways.
- [W2] the **source type** as described in [D1] with input from [W1].
- [W3] the raw water storage; this may be a reservoir (typical for a natural catchment), a harvest pond for a stormwater system, a tank (for example for a recycled wastewater system) or an aquifer for groundwater. Associated data including **capacity, a volume curve, elevation, height and diameter** is required.
- [W4] characteristics of available pumps such as performance curves (head, efficiency, and power against flow), cost, rated speed and variable speed pump (VSP) information where applicable.
- [W5] the **pump** transferring water from the raw water storage to a treatment facility, requiring data from [W4].
- [W6] pipe size and material information such as available diameters, unit costs, pipe wall roughness, wall thickness and embodied energy. For new pipes, this information will be easily obtained from the pipe manufacturer. For existing systems, however, there may be some uncertainty in these parameters if detailed records of the ‘as constructed’ system and any pipe replacements have not been kept. In addition to this, the pipe wall roughness of existing pipes will generally be uncertain. Pipe wall roughness increase as pipes age, and pipe condition assessment may be needed to provide an estimate.
- [W7] the **pipe system** transferring water from the raw water storage to the treatment facility, **pipe lengths and layouts** need to be known as well as information from [W6].
- [W8] the **treatment facility** that will produce water of the required quality based on the source type and demand type. Characteristics of the individual treatment methods as described in [D2] need to be known.
- [W9] the **pump** transferring water to a treated storage, requiring the same data as [W5].
- [W10] the **pipe system** transferring water to a treated storage, with the same information as [W7] required.
- [W11] the **treated storage**, for example, a tank or multiple tanks that are typically at a high elevation point of the network in order to supply demands by gravity. Data required includes the **elevation, height, diameter** and maximum and minimum allowable water levels.

[W12] the **pipe system** transferring water from the treated storage to consumers, which again requires information as in [W7]. This pipe system is likely to be more complex than those in [W7] and [W10], particularly for systems with many different demand nodes. For systems with only one source of water, [W7] and [W10] are likely to be single pipelines. For decentralized systems with only one specific consumer, [W12] will also most likely be a single pipeline. Most systems, however, have much more than one demand point and as such distribution systems are often looped or branched systems that require more complex analysis than single pipelines.

[W13] demand scenarios that will be applied to the demand nodes, consisting of a pattern of demand multipliers over a day, week or year. There may be multiple demand scenarios required for a system, for example, if there are different types of demand nodes (such as domestic, commercial, industrial) or different seasonal demands.

[W14] the peak demand is the demand rate that is typically used to size the system components and so will affect the design of the system. The demand scenarios [W13] are more likely to affect the operation of the system as the demand varies over the simulation time. The peak day demand (average demand over the peak day), the peak hour demand (the average demand over the hour with maximum consumption in the peak day) and average demand rates may also be required. Fire loading demands and other emergency conditions will affect the design of the system, for example storage tanks should be sized to be able to provide demand in the case of fires, other emergencies and system failures (e.g. if the supply to the tank is cut off).

[W15] the demand nodes for the consumers, these may be different types of users as described in [D4] and require information from [W13] and [W14]. Different types of users will have different demand rates [W14] and demand patterns [W13]. When simulating the system, an average demand rate will often be used with the demand pattern, rather than the peak demand. Systems with multiple demand nodes may prioritize different types of demands over other, for example, irrigation systems using non-potable water may prioritize high profile sport fields over reserves with no formal usage.

Choices made in the optimization of the design decisions sub-component [D] in Figure 5.1 will be inputs to the water system infrastructure sub-component. There may be other parameters that are not decision variables in the optimization (as differentiated in Table 5.1) though are still required by this sub-component in order to simulate the system. The construction and maintenance costs of each of the infrastructure components needs to be known in order to calculate the initial construction cost and ongoing costs as part of life-cycle economic costing. Information collected through this sub-component will be input to the simulation sub-component [S] depending on the types of simulation models used and to the evaluation sub-component [E] through the construction cost or other factors calculated for the specific objectives of a problem.

Electrical Energy Infrastructure Sub-Component [P]

The electrical energy infrastructure sub-component includes any power infrastructure that affects the electricity prices and GHG emission factors. The critical aspects of this sub-component as shown in Figure 5.1 and Table 5.1 are:

[P1] the breakdown of power sources including fossil fuel sources such as coal and oil, and renewable sources such as solar, wind and hydrothermal.

[P2] the electricity price tariff structure, which may be a peak and off-peak structure, or multi-part (more than two price levels) and could include a peak demand charge which applies to the peak electricity power usage in each month.

[P3] the GHG emission factor, which is based on the power source breakdown [P1] and may vary with time, either in the short-term (with sources that do not have storage such as solar panels and wind turbines) or the long-term (as fossil fuel sources tend to be phased out and renewable sources become more popular).

Climate and energy policy [G5] in the government policy component in Figure 5.1 will affect the power source breakdown and electrical energy pricing now and into the future. This is likely to be regulated by a federal government department or body. Information from this sub-component is used to calculate electrical energy costs in order to evaluate life-cycle economic costs and also to calculate life-cycle GHG emissions in the evaluation sub-component [E].

5.3.3 Government Policy Component [G]

The government policy component covers policies by regulating bodies at any level (local, state, federal) that may affect other aspects of the framework. These policies need to be considered over the operational life-span of the system, for example, climate and energy policy may affect future energy sources and therefore affect future GHG emissions. The critical aspects of this component as shown in Figure 5.1 and Table 5.1 are:

[G1] fit-for-purpose water use, which may be regulated by state or federal governments or health agencies and affects which water sources [D1] and water uses [D4] can be combined in the design decisions sub-component. It may also guide which design decisions (for example, treatment) are appropriate.

[G2] water source licenses, which may be regulated by local or state governments or the environmental protection agency, depending on the catchment size, and will affect the amount of water available from particular sources for allocation in long-term operations [O4].

[G3] environmental flows, which similarly to water source licenses may be regulated by local or state bodies depending on the size of the catchment and affect the amount of water available for allocations [O4].

[G4] the discount rate applied to operational costs and GHG emissions in life-cycle analysis [E1]. This is unlikely to be set by a government body and rather will be informed from outside the decision making team, generally by recommendations from economists.

[G5] climate and energy policy set by state and federal governments will affect the energy sources available now and in the future, therefore affecting GHG emission factors and any GHG objectives [P].

5.3.4 Analysis Component [ANL]

The analysis component uses information from the options, infrastructure and government policy components to simulate the system and evaluate how it performs relative to the objectives and constraints. Within an optimization algorithm, the analysis component is used to assess multiple combinations of decision variables from the options component to determine how they perform. There are two sub-components within the analysis component; the simulation sub-component [S] and the evaluation sub-component [E]. The simulation sub-component includes the modeling aspects of the problem and the key variables that are required to be output from the models in order to evaluate the system. Optimization objectives and constraints are defined in the evaluation sub-component, which also provides information to the optimization algorithm as to which of the potential solutions perform best.

Simulation Sub-Component [S]

The simulation sub-component considers the type of simulation model that is most applicable to the particular system and problem, and specifies the key variables that need to be calculated in the model(s). The critical aspects of this sub-component as shown in Figure 5.1 and Table 5.1 are:

- [S1] the hydrologic simulator, which is required if rainfall scenarios need to be transformed to streamflow, typically for systems using natural catchment water or harvested stormwater.
- [S2] the mass balance model, which may be required for systems that have multiple water sources with long-term allocation decisions, particularly if there are different rainfall and evaporation scenarios to be considered for the storages.
- [S3] the WDS hydraulic simulator, which is required to analyze pump and pipe systems that transfer water between different storages and treatments and to consumers.
- [S4] information on constraints, such as yield from a hydrologic model, environmental releases and system reliability from a mass balance model, and nodal pressures, pipe velocities, pump switches and tank levels from a hydraulic model.
- [S5] the water levels in storages, which are important particularly when considering operational decisions, such as trigger levels, and for constraints, such as system reliability.
- [S6] the power usage from any pumps or treatment facilities, which are important in informing the ongoing electrical energy costs as part of life-cycle economic costing. Generally a WDS hydraulic simulator is required to model detailed pump operations and therefore accurately estimate the pump power usage.

Each of the three types of models will require different simplifications or assumptions depending on the particular system. For example, mass balance modeling will generally only consider one pump operating point so may not accurately calculate the pump power usage. When deciding which type of model to use for a particular problem, the user will need to consider the different simplifications, assumptions, advantages and disadvantages of each model. Trade-offs between accuracy of outputs and simulation run times need to be considered. For example, when optimizing both short- and long-term operations of a system, there is likely to be a trade-off between using a hydraulic simulator for detailed hydraulic information and using a mass balance model for shorter run times. Most problems may ideally use elements from more than one type of model; however, using multiple models will increase computational complexity and run times. Wherever possible, the most applicable type of model should be selected and augmented with the required elements from other types of models. Depending on the particular system and optimization problem, there may be other key variables that need to be calculated in the simulation models. For optimization of pumping operations, which is the focus of the case studies in this paper, storage water levels and pump power usage are the most important. Existing hydrologic, mass balance and hydraulic simulators, for example, MUSIC, WATHNET and EPANET, have often been used in conjunction with optimization algorithms and should be taken advantage of where possible rather than creating individual simulators for different problems.

Information from the operation decisions sub-component [O] will be input to the simulation sub-component as the overall operating strategy for the system ([O3] and [O4]) will need to be modeled. Short-term operations are likely to be considered in a hydraulic simulator and long-term operations, including allocations, in a mass balance model. Parameter data on the physical components of the system from the water system infrastructure sub-component [W] are also required as inputs for this sub-component. Constraint information is provided to the evaluation sub-component to compare the systems performance against specified requirements. Energy usage is used to calculate objective functions such as life-cycle economic costs and life-cycle GHG emissions. Simulating systems prior to optimization is an important step to help inform the formulation of the optimization problem and provide a check that results from the optimization are reasonable.

Evaluation Sub-Component [E]

The purpose of the evaluation sub-component is to compare the performance of each of the potential solutions to the objectives and constraints of the problem. The critical aspects of this sub-component as shown in Figure 5.1 and Table 5.1 are:

[E1] the specific objective(s) to be considered in the optimization; typically, minimizing life-cycle economic cost is a primary objective (or a component of that such as construction cost or operational cost individually). Other possible objectives include minimizing spills from reservoirs and other storages, minimizing life-cycle GHG emissions (or a component of that such as embodied energy from construction or operational emissions), minimizing supplemental potable water supply (in systems using non-potable sources), maximizing water quality, maximizing reliability and minimizing environmental impact.

[E2] the objective function(s) to be optimized; multiple objectives may be evaluated as individual functions in a multi-objective optimization algorithm or combined into a single function for use in a single objective optimization algorithm. It is important to consider how each objective should be formulated, for example, when optimizing short-term pump operations to minimize ongoing costs, the objective function may be evaluated in terms of cost per volume of water pumped, as this will take into account the amount of water delivered to consumers. Reliability of a system may be formulated in different ways, for example minimizing the time spent with water restrictions applied or minimizing the time spent below a certain storage level. Some objectives may be more difficult to quantify, such as minimizing environmental impact, so more specific objectives may be required, for example, maximizing environmental flow or minimizing the change in a water body's natural hydrological regime. Simplifications and assumptions may be required to formulate some objectives as mathematical functions. When performing multi-objective optimization, trade-offs between the different objectives should be considered by the development of Pareto fronts, allowing the decision maker to determine which Pareto optimal solution best fits their needs (see examples in Wu et al. 2010a, 2010b, 2012a, 2012b, 2013).

[E3] the specific constraints to be considered as described in [S4].

[E4] the evaluation of the constraints compared to the limits set by the user; maximum and/or minimum values for each constraint need to be specified. Some constraints may be flexible, for example, if an environmental flow is set by a regulator, the operator could consider increasing the set environmental flow as a decision variable in the optimization. There are several different ways constraints can be incorporated into the optimization algorithm. Penalty functions are often used for single-objective problems. They add value (often a monetary amount) to the objective function in a minimization problem and remove value from the objective function in a maximization problem based on the magnitude of the constraint violation, therefore making solutions that violate constraints less desirable (Nicklow et al., 2010). Care must be taken when formulating penalty functions to keep solutions that only slightly violate constraints in consideration during the optimization process, while ensuring the feasibility of the final optimal solutions. For multi-objective problems, a constraint-handling technique that will ensure feasible solutions are retained in preference to infeasible solution is often employed. An example of this is the constraint tournament selection procedure introduced by Deb et al. (2002).

Information about the objectives is received from the simulation sub-component [S] and from the calculation of construction, maintenance and electrical energy costs based on the water system infrastructure sub-component [W] and simulation sub-component. A discount rate for costs or GHG emissions may be set in the government policy sub-component [G] which will impact the ongoing costs and emissions in a life-cycle analysis. The discount rate may be informed by economists, such as the Stern review which recommends low discount rates for projects that lead to the production of GHG emissions (Stern 2006). Information about the performance of each potential solution in relation to the objectives and constraints is provided to the optimization algorithm in order to find the best solutions.

5.3.5 Optimization Algorithm [OA]

The optimization algorithm is used to determine which solution(s), out of many potential solutions to the problem, performs best in relation to the objective function(s). The procedure used to set up the optimization will depend on the type of algorithm chosen; however, the first step is generally to define the decision variables, objectives and constraints of the problem. This will then guide what aspects of the system need to be modeled and what data is required in order to take into account all of the decision variables and that will provide information for all of the objectives and constraints. Multiple potential solutions to the problem form the 'solution space' and the optimization algorithm guides the search of this solution space towards the global optimum. The size of the solution space depends on the number of decision variables and number of choices available for those decision variables. More complex problems are often described as having a more 'rugged' solution space, meaning the optimization algorithm is more likely to get trapped in local optima and will have more difficulty finding the global optimum. When a single objective optimization algorithm is used, one optimal solution will be found, while in multi-objective optimization, a Pareto front will be developed with multiple solutions representing different trade-offs between the objectives.

Most optimization algorithms have parameters that need to be defined by the user, such as the number of generations or iterations and the population size in evolutionary algorithms. Although the choice of these parameters does not influence the components shown in Figure 5.1, they have an effect on the optimal solutions found by the algorithm. In general, the most effective set of parameter values to use will vary between different optimization problems and the size of the solution space can only give some indication of what parameter values to use. In fact, multiple parameter sets should be tested in order to find the most appropriate values for the specific problem. Ideally, the chosen parameter set should find the same optimal solution regardless of the starting point or initial solution(s) for the optimization. Dandy et al. (1996) presented an improved genetic algorithm formulation for optimization of WDS design. Five different parameter sets were trialed on both their improved genetic algorithm and a comparatively simple genetic algorithm. They acknowledged that parameter selection does require some judgement on the part of the user, however, they found their optimization results to be relatively insensitive to the parameter choice, particularly for the improved genetic algorithm. As well as the effect of various parameter values, different optimization algorithms will be more suited to different problems. This issue has been addressed by the development of hybrid algorithms, such as AMALGAM (a multi-algorithm, genetically adaptive multiobjective approach proposed by Vrugt and Robinson (2007)), which combines several different optimization algorithms to improve search efficiency. These hybrid algorithms also have the benefit of requiring little to no parameter specification by the user.

5.3.6 Sensitivity Analysis

As identified in Table 5.1, values of some input parameters (for example, describing the network or water demand loadings) are uncertain or subject to change in the future. Sensitivity analysis can be performed to account for a wide range of possible future conditions when optimizing and simulating systems. Variation of a particular parameter may result in different Pareto fronts (in multi-objective optimization) or different optimal solutions (in single objective optimization), as seen in Wu et al. (2010b) when they considered variations in discount rates. These various Pareto fronts or optimal solutions along with the various parameter values that produced them can then be provided to the decision maker. Sensitivity analysis will also help to identify if there are any uncertain parameters that do not affect the optimal results. Robustness of the optimized solutions can also be explored a-posteriori: in general, solutions that perform well for many different possible conditions are more desirable from the decision makers' point of view. Climate change provides an additional source of uncertainty for the parameters identified in Table 5.1 – detailed discussion of this is omitted from Sections 5.3.6.1 to 5.3.6.4 as it is covered in Section 5.3.6.5.

<u>Demand</u>

In some applications, such as irrigation and agriculture, the demand rate and pattern may be deterministic [O1], either the water supplier has control over the consumption, or may be able to work with those who do to determine an optimal demand schedule. For other applications, such as domestic, commercial and industrial, the demand rate and pattern depends on the consumption of water by multiple individual users [D4, W13, W14, W15], and therefore has greater uncertainty. Historical consumption can provide some level of assurance as to how water may be used in the future, at least on an aggregated scale. Diurnal, weekly and seasonal demand variations need to be considered. In the future, factors such as climate change, population growth and water saving initiatives will affect how water is consumed and therefore impact demand rates and patterns. Emergency conditions and system failure are by their nature unpredictable and this should be taken into account when designing and operating WDSs.

An example of how demand uncertainty can be considered in the optimization of WDS design is the study by Basupi and Kapelan (2015). The demand at each time step was based on a normal distribution with a gradually increasing mean (based on deterministic demand forecasts) and an increasing standard deviation. Monte Carlo or Latin Hypercube simulation was included in their methodology to consider multiple demand scenarios. Each solution in the Pareto front was also further analyzed against three demand projections – average, optimistic (low overall demand) and pessimistic (high overall demand). Their results demonstrated the value of flexible WDS design over deterministic approaches when considering uncertainty.

<u>Rainfall and Streamflow</u>

Rainfall and streamflow inputs [W1] may be required for systems using natural catchment water, harvested stormwater or imported water, and they are often treated with higher uncertainty than demands (Seifi and Hipel, 2001; Reis et al., 2005). Within the current climate, there may be multiple realizations of possible rainfall and streamflow series (for example dry or wet years). Beh et al. (2015) considered rainfall, as well as population and temperature, as uncertain variables in their optimal sequencing methodology for water supply system augmentation. They considered both climate and hydrologic variability: seven possible future climate scenarios provided different forecasted rainfall reductions, and within each of these seven scenarios, 20 stochastic replicates of the rainfall sequence were produced. Different Pareto fronts were produced for each climate scenario, with the more severe scenarios finding solutions that required greater system augmentation and therefore had higher costs and GHG emissions. The robustness of each Pareto solution was calculated based on the average reliability and vulnerability of the solution over the 20 rainfall sequences for the particular climate scenario.

Electricity and GHG Emissions

Power source(s) [P1], electricity tariffs and costs [P2] and GHG emission factors [P3] will generally be known for the present time, however, it may not be clear how they will change in the future. The mix of power sources changes naturally over time, as different power plants are built or decommissioned. This change in power source types over time, as well as technical advancements will affect the cost and GHG emissions associated with electrical energy generation. The electricity market and economic factors will also affect the cost of electrical energy over time. Changes in electricity and GHG emissions can be an important factor to consider during an optimization problem, as shown in the following examples. Blinco et al. (2014) studied the optimization of pump operations in WDSs in relation to the minimization of GHG emissions and the use of different power source scenarios, showing that optimal tank trigger levels can be influenced by the variation in emission factors. Wu et al. (2012a) considered three different electricity tariff scenarios, which increased over time, and three different GHG emission factor scenarios, which decreased over time, in the optimization of WDS design. The different electricity tariff and emission factor scenarios affected the solutions found in the Pareto front and their overall costs and GHG emissions.

Discount Rate

A discount rate [G4] may be used in life-cycle analysis for both ongoing economic costs and ongoing GHG emissions. In practice, discount rates on economic costs vary significantly between different organizations, generally from 2% to 10% (Rambaud and Torrecillas, 2005), while many water utilities use discount rates in the range of 6% to 8% (Wu et al. 2010a). When selecting discount rates, consideration should be given to whether both economic costs and GHG emissions are discounted, if they have the same discount rate, and if intergenerational equity is taken into account using social discount rates. Various social discount rates have been proposed for discounting ongoing costs; the Intergovernmental Panel on Climate Change (IPCC) adopted a zero discount rate over a period of 100 years, after which no consideration for future costs or benefits is given (Fearnside 2002), other suggestions include 1.4% (Stern 2006) for projects that are impacted by climate change, 2-4% (Weitzman, 2007) and a time declining rate (Gollier and Weitzman, 2010). Wu et al. (2010b) gave an example of a sensitivity analysis of discount rates in the optimization of WDS design for minimization of costs and GHG emissions. Discount rates of 0%, 1.4%, 2%, 4%, 6%, 8% and a time declining rate were applied to the economic costs, with GHG emissions either not discounted at all, or discounted at the same rate as costs. They found that the different discount rate scenarios produced different Pareto fronts; when GHG emissions were discounted, the solutions tended to have lower capital costs and higher operating emissions.

Climate Change

Management of water resources in the developed world has been based on an assumption of stationarity – that is, ‘that natural systems fluctuate within an unchanging envelope of variability’ (Milly et al. 2008). The effects of human-induced climate change make this assumption no longer valid (Milly et al. 2008), and introduce additional sources of uncertainty for many parameters. Uncertainty introduced by climate change is twofold – firstly, the impacts of climate change increase the uncertainty of future weather conditions; and secondly, our response to the threat of climate change and the types of adaption methods that will be utilized in the future are uncertain. Climate change affects the magnitude and temporal and spatial distribution of rainfall, temperature and other environmental factors, thus the possible rainfall and streamflow series to consider for the future will likely be different to the present. Changes to temperature and other environmental factors will also affect the hydrology of natural and urban catchments and therefore change how rainfall will transform to runoff or streamflow. Climate change impacts will also affect how people consume water, for example, higher temperatures and lower rainfall may drive people to water their gardens more. In order to simulate future climate conditions, general circulation models (GCMs) are often used in conjunction with future emissions scenarios. According to Mpelasoka and Chiew (2009), 'GCMs are the best tools available for simulating global and regional climate systems', however, the information provided is generally too coarse for applications to catchment runoff, and therefore some kind of downscaling is required. The modeling uncertainty of both the GCMs and downscaling methods increases the uncertainty of future climate scenarios (Paton et al., 2013). In 2000, the IPCC introduced several emissions scenarios (termed SRES scenarios) projecting future global GHG emissions. The various scenarios are based on different assumptions of the mix of energy generating technologies (fossil fuel or non-fossil fuel dominant) and population, economic and technological growth (IPCC 2007).

The extent to which we can reduce our GHG emissions will affect the magnitude of climate change impacts on rainfall and temperature. With the growing concerns of climate change and sustainability, renewable sources such as solar and wind will become more prevalent and replace fossil fuel sources such as coal and gas. This may affect electricity pricing and GHG emissions from power generation. Multiple future power source scenarios assuming different levels of climate change mitigation may need to be considered. Other climate change adaption strategies include economic incentives such as carbon taxes and cap and trade systems, which may affect economic analysis of WDSs. As discussed in Section 3.6.4, when climate change and intergenerational equity are considered, social discount rates of 0%, 1.4%, 2-4% and time declining rates have been proposed.

Paton et al. (2013) analyzed the sources of uncertainty relating to climate change and their impact on water supply security. They considered 19 different scenarios with different combinations of six SRES scenarios, seven GCMs and six demand projections, as well as 1000 stochastic rainfall replicates. They found that the impact of the different sources of uncertainty on the optimal solutions varied over the 40-year planning period, with some having a greater effect in the short-term and others a greater effect in the long-term. Roshani and Filion (2014) investigated the impact that different climate change abatement strategies have on water main rehabilitation. They consider six carbon abatement strategies with different combinations of two discount rates (1.4% and 8%) and three carbon tax scenarios (no tax, 'fast and deep', and 'slow and shallow'). Using a low discount rate and implementing a carbon tax encouraged the optimization algorithm to find solutions that invested in rehabilitation early, to reduce the cost of continuing leaks, pipe repair, energy use and GHG emissions.

5.4 Case Studies

The utility of the framework described in the previous sections will now be explored by two different case studies that have different water sources and many variables that need to be considered. These case studies are provided as an example of how the framework could be applied to optimize system operations. The first case study is a managed aquifer recharge (MAR) system that harvests stormwater from an urban creek for irrigation of reserves and sporting fields. This case study demonstrates the importance of analyzing the system by simulation prior to optimization in order to formulate the optimization problem. The second case study is a water supply system in a rural town that supplies potable water from multiple alternative water sources. This system is optimized for minimization of energy use of the many pumps used to transfer water from the various sources.

5.4.1 Ridge Park Managed Aquifer Recharge – Case Study 1

Ridge Park is located in the Adelaide metropolitan area in South Australia, within the City of Unley local government area. The scheme supplies harvested stormwater to sports fields and recreational reserves in the local area for non-potable irrigation use. The scheme is designed to harvest up to 60 ML of stormwater per year, which occurs over the winter, while in summer the harvested water is used for irrigation. During winter, stormwater from Glen Osmond Creek, an urban waterway, is collected in the Harvest Pond created by a dam on the creek (Figure 5.2). Water is then pumped to the Bioretention Basin which provides some treatment, and then pumped to a small treatment plant that includes UV and filtration. Once the water has been adequately treated, it is stored in an above ground tank next to the treatment plant and final pump station. From the Storage Tank, water is injected into an artesian, fractured rock aquifer for long term storage. In summer, when no water is being harvested, water is extracted from the Aquifer and to the Storage Tank, before being pumped or gravity-fed to irrigation points. The Ridge Park Reserve is irrigated by a pressurized irrigation line, as it is at higher elevation than the Storage Tank. Fraser Reserve is also connected to the pressurized system to ensure adequate pressures for irrigation. In total, the pressurized system supplies almost 15 ML of water per year. The remaining seven reserves are on a gravity-fed line which supplies a total demand of roughly 35 ML per year. The layout and details of the system are given in Figure 5.3. For more detailed data on this case study, please see Appendix E.

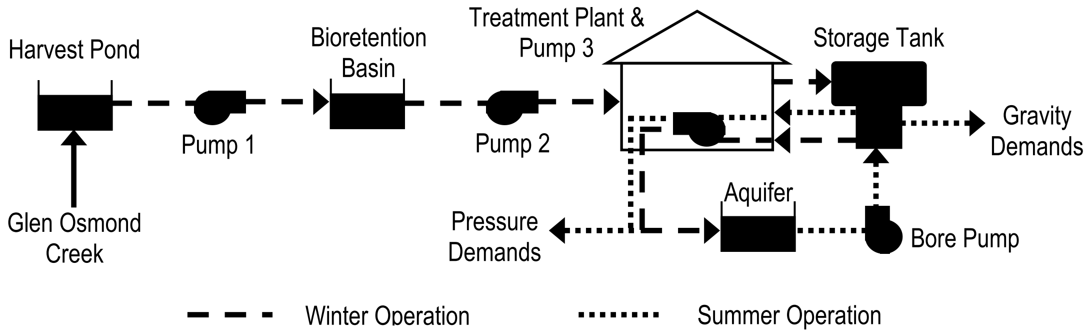


Figure 5.2: Ridge Park Managed Aquifer Recharge System process schematic

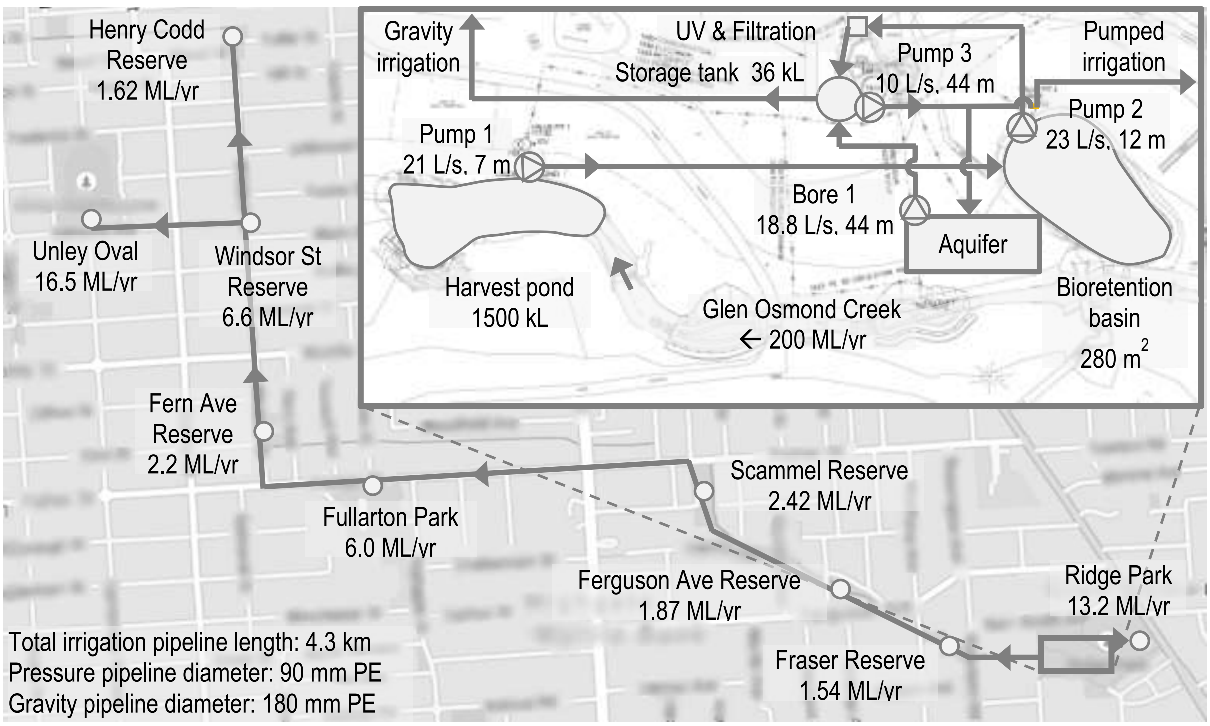


Figure 5.3: Ridge Park Managed Aquifer Recharge System layout and data

For existing systems, simulation analysis of the current operation is an important first step in formulating the optimization problem. Results of current operational simulations can highlight areas for improvement that can then be focused on in the optimization. The operation of the Ridge Park stormwater harvesting system was split between winter and summer operations and both were simulated in EPANET to determine current pump operational costs. Trigger levels (related to volumes in the three storages as shown in Table 5.2) control when the pumps in the Winter Harvesting and Injection system turn on and off (Table 5.2). The Bore Pump is also controlled by trigger levels in the Storage Tank. During summer, Pump 3 is controlled by the irrigation demands, which are on a schedule so that different reserves are irrigated on different nights (Table 5.3). Pump 3 is a VSP and is operated at 80% of full speed for injection (such that the flow is less than the 7 L/s maximum for injection) and 75% of full speed for irrigation (such that the target pressure downstream of the pump is achieved at the expected demand rates). Both systems were simulated for a period of one week in EPANET, with a 15 minute hydraulic time step and five minute reporting time step. Several week-long streamflow series for the available flow in Glen Osmond Creek at a daily resolution were used in the harvesting and injection model (Figure 5.4). A peak/off-peak electricity price tariff applied to the entire system; a peak price of 25.53 c/kWh was applied from 7am to 9pm on weekdays, and an off-peak price of 15.26 c/kWh was applied over night and on weekends (tariff pattern and simulations started on a Sunday).

Table 5.2: Trigger levels for the Ridge Park System

Storage and Trigger Level Type	Current Setpoint		Start Pump	Stop Pump
	Volume (%)	Level (m)		
Harvest Pond High Level	80	1.6	1	-
Harvest Pond Low Level	50	1.0	-	1
Biofiltration Basin High Level	90	0.80	2	1
Biofiltration Basin Low Level	50	0.59	-	2
Storage Tank High Level	90	2.25	3	2, Bore
Storage Tank Low Level	70	1.75	Bore	3

Table 5.3: Irrigation demand schedule for the Ridge Park System

Reserve	Demand Rate (L/s)	Duration/day (hr)	Start Time	Irrigation Days
Ridge Park 1	3.53	8.33	9:30 PM	Mon & Wed
Ridge Park 2	3.53	8.67	9:30 PM	Tues & Thurs
Fraser Reserve	1.41	5.83	9:30 PM	Mon & Wed
Ferguson Ave Reserve	2.00	5.00	9:30 PM	Tues & Thurs
Scammell Reserve	2.15	6.00	10:00 PM	Tues & Thurs
Fullarton Park 1	3.85	1.67	10:00 PM	Mon & Wed
Fullarton Park 2	3.85	6.67	10:00 PM	Tues & Thurs
Fern Ave Reserve	3.53	3.33	10:00 PM	Mon & Wed
Windsor St Reserve	2.20	8.00	8:30 PM	Tues & Thurs
Henry Codd Reserve	1.10	8.00	10:00 PM	Mon & Wed
Unley Oval	5.57	9.00	9:00 PM	Sun, Mon & Wed

Winter Harvesting and Injection System current pumping operation results

When there was adequate water available, such as in Streamflow Series 1, 4 and 5, the volume of water injected into the aquifer (by Pump 3) was a little over 3 ML per week (Table 5.4). This was significantly less than the volume available, which reflects the limited flow rate of Pump 3 (7 L/s for injection to the aquifer), as well as the water that would be lost to overflow when the inflow rate is greater than the flow rate of Pump 1 (approximately 22 L/s). The total pump energy cost estimate for the harvesting and injection system ranged from $163 to $267 per week, with an average of $235 per week. Pump 1 was the most cost-effective to run, while Pump 3 was the most expensive. Pumps 1 and 2 operated at similar times throughout the day, however, Pump 2 has much lower efficiencies, which increased its energy use. Pump 3 operated at a lower flow rate but much higher head than Pumps 1 and 2, and was more likely to be switched on for the entire day, which contributed to its higher cost of operation. Pumps 1 and 2 turned on and off very frequently, and operated at a much higher flow rate than Pump 3 (Figure 5.5). The flow rate of Pump 3 in Figure 5.5(c) reduced over the week as the headloss through the bore increased from assumed clogging of the bore. As the storages are relatively small, in particular the storage tank, it did not take long for them to be filled and emptied (Figure 5.6), which contributed to the frequent pump switches. The current trigger levels in the Storage Tank are very close together (70% and 90% volume) as a result of possible pump priming issues that occurred during the commissioning of the system. These close together trigger levels also contributed to the short fill and empty times.

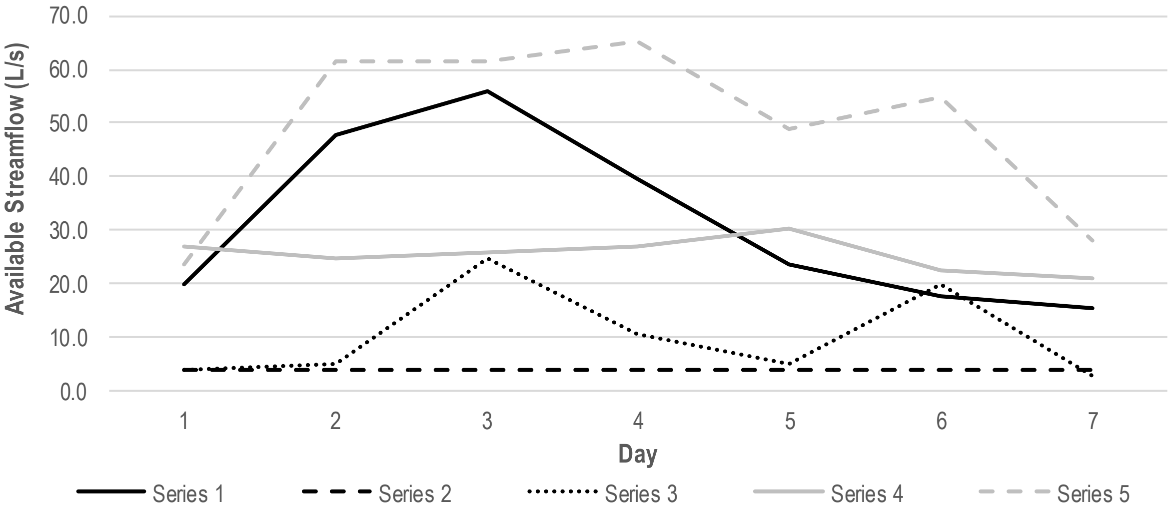


Figure 5.4: Streamflow series used for simulation of the Winter Harvesting and Injection operation

Table 5.4: Current operation results for the Winter Harvesting and Injection System

Streamflow Series	Available Volume (ML/wk)	Cost (c/kL)			Volume Injected (ML/wk)	Total Cost ($/wk)
		Pump 1	Pump 2	Pump 3		
1	19.0	0.64	2.28	5.49	3.14	267
2	2.29	0.68	2.32	6.19	1.76	163
3	6.19	0.69	2.23	5.87	2.44	222
4	15.4	0.64	2.24	5.46	3.18	258
5	29.7	0.63	2.25	5.47	3.16	264
Average	14.5	0.66	2.26	5.70	2.74	235

Summer Extraction and Irrigation System current pumping operation results

Simulation of the irrigation system gave a total weekly pump energy cost of $90 (Table 5.5). The Bore Pump was more expensive overall, however, cost less per megaliter than Pump 3. This occurred because while the Bore Pump has a greater efficiency than Pump 3, it also has a higher flow and head, which increased the energy consumption. The higher volume pumped from the bore contributed to a lower cost rate than Pump 3. All of the pumping for this system occurred overnight (Figure 5.7) when irrigation of all fields is allowed. The Bore Pump turned on and off very frequently when it was operating, again due to the small capacity of the Storage Tank which meant it did not take long for the pump to fill the operating volume (Figure 5.8).

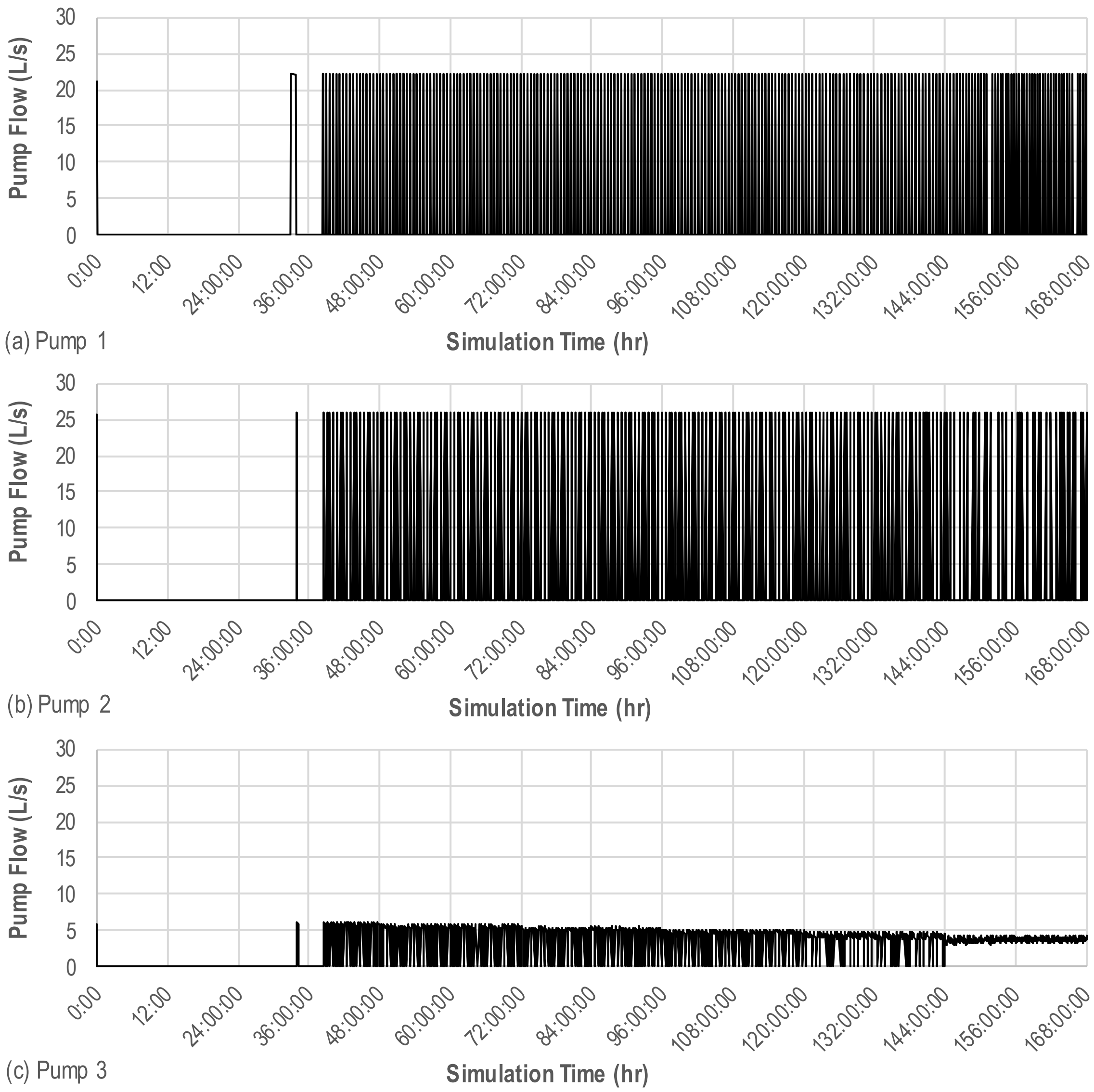


Figure 5.5: Pump flows for Streamflow Series 2 for (a) Pump 1, (b) Pump 2 and (c) Pump 3 for a one week EPANET simulation

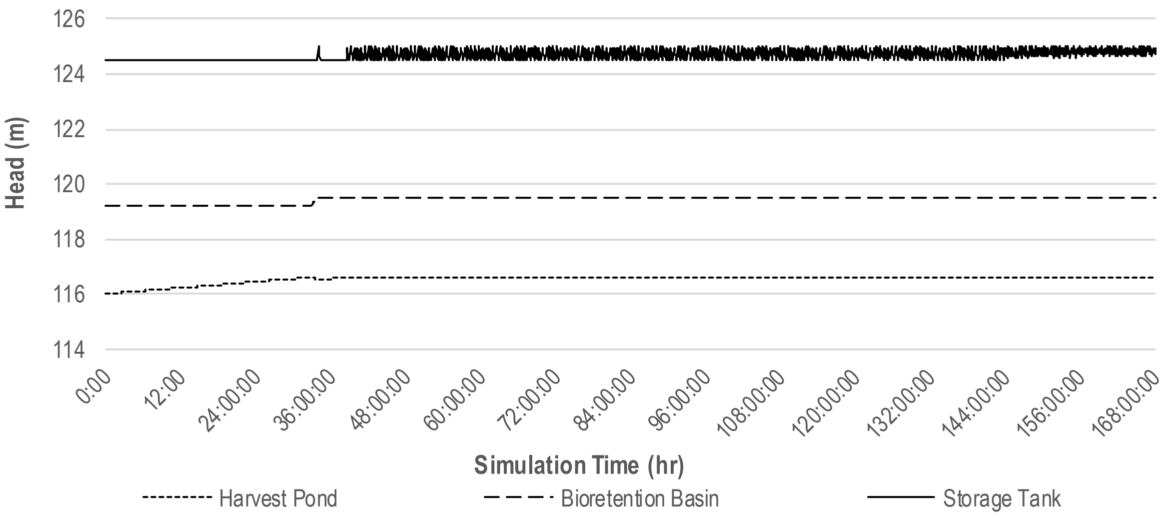


Figure 5.6: Storage levels for Streamflow Series 2

Table 5.5: Current operation results for the Summer Extraction and Irrigation System

Pump	Volume (ML/wk)	Cost (c/kL)
Bore Pump	1.93	3.52
Pump 3	0.57	3.97
Total		$90.3 / week

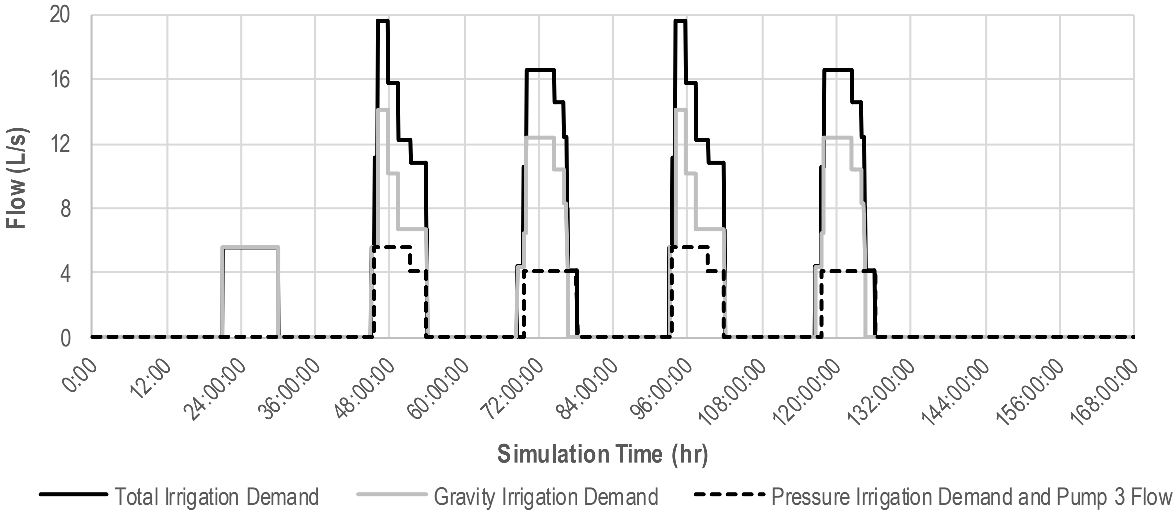


Figure 5.7: Current demand rate and pump flows for the Irrigation System

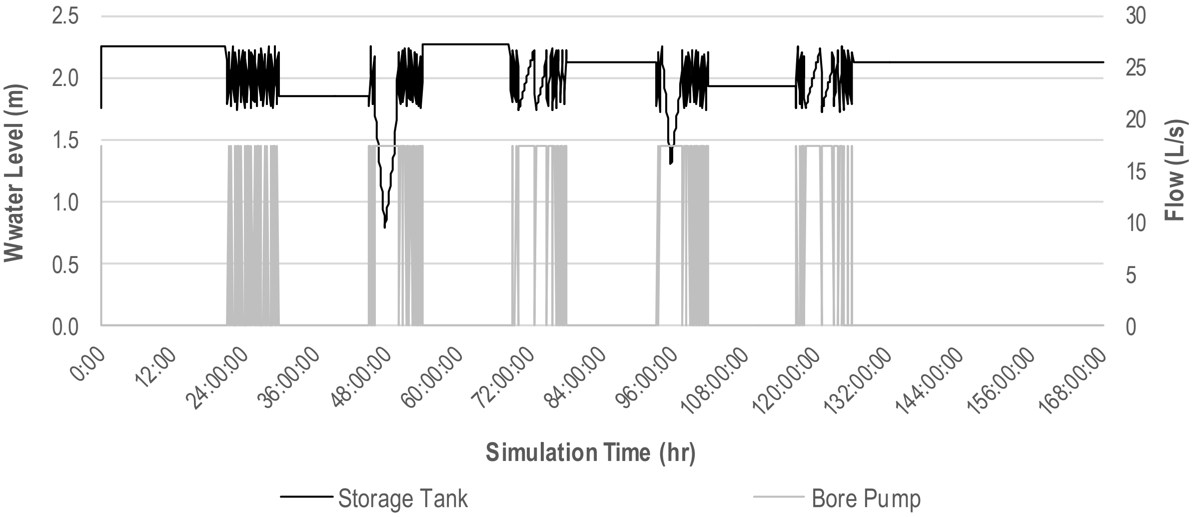


Figure 5.8: Storage Tank level and Bore Pump flow for the Summer Extraction and Irrigation System

Optimization Formulation

Initially, optimization of the Ridge Park system was considered to be an operational problem, however, results of the current operation simulation suggest that design decision variables need to be considered as well. Replacing Pumps 1 and 2 with models that would operate at much lower flow rates (to reduce the headlosses) and increasing the size of the Storage Tank will be considered along with operational decision variables (Table 5.6). These design decisions would aim to counter-act mismatched pump rates (Pumps 1 and 2 operating at a much higher rate than Pump 3) and small storage volumes that lead to frequent pump switches. Short-term operational decisions include trigger levels in the Harvest Pond, Bioretention Basin and Storage Tank that will govern when pumps are turned on and off, a schedule for irrigation (that is, which reserves will be irrigated at which times), and VSP multipliers for Pump 3. In the current operation, VSP multipliers for Pump 3 were selected to ensure the required flow rate (for injection) and pressure (for irrigation) were achieved. With different levels in the Storage Tank considered, the VSP multipliers for Pump 3 can be altered, especially if efficiency is improved. If the pump priming issues discussed earlier were to be resolved, trigger levels that utilize the full height of the Storage Tank (rather than the 20% range in water elevation that is currently used) would be considered in the optimization. There are also long-term decision variables deciding when to switch between summer and winter operation and vice versa (Table 5.6). As the scheme injects to and extracts from the aquifer through the same bore, it is not possible to frequently switch between injecting and extracting water, therefore there will be only two switch times per year; one going into winter operation and one going into summer operation. The decision variables presented in Table 5.6 may all be considered together in an optimization problem, however, they could also be analyzed prior to optimization in a simulation sensitivity analysis. Simulating the system initially with the different pump models and storage tank sizes could help to decide if these actions are worthwhile considering in an optimization formulation. Engineering judgement may be sufficient to determine which pump model(s) would be best to replace Pumps 1 and 2, and therefore reduce the size of the optimization problem.

Table 5.6: Possible decision variables for the Ridge Park MAR Scheme

SHORT-TERM WINTER HARVESTING AND INJECTION OPERATION	
Pump 1 Off	Harvest Pond Level Low Bioretention Basin Level High
Pump 1 On	Harvest Pond Level High
Pump 2 Off	Bioretention Basin Level Low Storage Tank Level High
Pump 2 On	Bioretention Basin Level High
Pump 3 Off	Storage Tank Level Low
Pump 3 On	Storage Tank Level High
Pump 3 Speed	Storage Tank Level
SHORT-TERM SUMMER EXTRACTION AND IRRIGATION OPERATION	
Bore Pump Off	Storage Tank Level High
Bore Pump On	Storage Tank Level Low
Irrigation Schedule	Days of Irrigation at each Reserve Start Time of Irrigation at each Reserve
Pump 3 Speed	Required Demand Rate
LONG-TERM OPERATIONS	
Day to Switch Between Seasonal Operational Regimes	Summer to Winter Winter to Summer
SYSTEM DESIGN	
Storage Tank Size	Doubled, 5 times, 10 times current size
Pumps 1 and 2	Selection of pump curves with lower operating rates

Constraints on the system include an environmental flow for Glen Osmond Creek, an extraction limit from the Aquifer and meeting the weekly irrigation volumes for each reserve in the summer (Table 5.7). If there was not enough water harvested over the winter to supply the summer demands, a potable back-up supply is available at a cost. The main objective for this case study is to minimize the pump energy cost; there is also a secondary objective of minimizing the number of pump switches. To create an incentive for the optimization to find solutions that harvest more water, the cost objective includes the energy cost for the harvesting and distribution operation as well as the cost of purchasing potable water if the harvested volume is not enough to supply demand. The objective function is formulated as the cost per volume of water harvested as another means to ensure enough water is harvested from the system during winter to supply summer irrigation. During the conceptualization and design of this scheme, regulations from the South Australian Environmental Protection Authority (EPA), the Department for Environment, Water and Natural Resources (DEWNR) and the Department of Health (DoH) were considered. A license to recharge water into the aquifer was required from the EPA, while the DEWNR regulates how much water can be extracted from MAR schemes. DoH regulations informed the level of treatment implemented and the irrigation practices, which must limit the risk of public exposure.

Table 5.7: Possible constraints for the Ridge Park MAR System

Constraint	Value
Glen Osmond Creek Environmental Flow	> 2 L/s
Aquifer Extraction in Summer	< 80% of Injection Volume
Pressurized System Demands	> 15 ML/year
Gravity System Demands	> 37 ML/year

5.4.2 Orange Integrated Supply System – Case Study 2

Orange is a rural town roughly 250 km west of Sydney in the state of New South Wales, Australia. The water supply system serves a population of around 36,800 people with an average annual demand of approximately 5,400 ML. The majority of water supply is from the local surface water catchment, which culminates in the roughly 19,000 ML Suma Park reservoir (Figure 5.9). Australia experienced severe drought between 2000 and 2010, and Orange was one of the hardest hit areas in New South Wales. Even with severe water restrictions almost halving the town's demand, Orange had less than 2 years of water supply heading into summer of 2009, and was relying only on surface water catchments (Montgomery Watson Harza, 2011). This prompted the Orange City Council to diversify their water supply, and they therefore developed two stormwater harvesting schemes and a long pipeline from an adjacent catchment, as well as re-opening several groundwater bores. Figure 5.9 shows a schematic process diagram of the system, which is described below, and Figure 5.10 shows the layout (note that the 'Shearing Shed' Bore and 'Bore 5' in Figure 5.9 are grouped as the 'Clifton Grove' Bores in Figure 5.10). For more detailed data on this case study, please see Appendix F.

Water from the Ploughman's Creek Stormwater Scheme is treated through a series of wetlands, and then combined with water from the Blackman's Swamp Creek Stormwater Scheme. After treatment, this water can be used to top up Suma Park reservoir. Due to the severely low water supply levels during the drought, Emergency Authorization was initially given, and Council subsequently sought approval for use of the stormwater schemes on a permanent basis. Continuous water quality monitoring is undertaken to meet regulations of the Office for Water, the New South Wales Environmental Protection Authority and the Ministry of Health. To the authors' knowledge, this is the only system in Australia that has been approved to use harvested stormwater for potable supply. In order to use harvested stormwater for potable supply, the Council had to meet requirements of the Office for Water. The Macquarie pipeline transfers water from the adjacent Macquarie River catchment to Suma Park reservoir. It is 38 km long and requires more than 600 m of pumping head. Each of the three pumping stations has two pumps operating in parallel. Water from the groundwater bores is pumped first to balancing storages and then to Suma Park reservoir, with a combined licensed volume of 462 ML per year. Water from all of the sources is combined in Suma Park reservoir and treated at a water treatment plant before being delivered to consumers.

The Orange City Council is interested in optimizing the operation of this while delivering a secure yield from Suma Park Dam. In addition to the primary objective of minimizing energy cost, there are objectives of minimization of spill from Suma Park reservoir, minimization of (perceived) environmental impact, maximization of (perceived) water quality, and minimization of energy use. The Council has an explicit objective to minimize spill to ensure water and energy are not wasted by pumping from one of the three alternative sources to fill up Suma Park reservoir just before a rainfall event that would supply water from the natural catchment at no cost or energy output. As this system supplies potable demands, it is undesirable to apply water restrictions to consumers, thus minimizing time spent in restrictions is important. Objectives for the perceived environmental impact and water quality will be formulated as a preference ranking between the different sources based on community views of which sources are better for the environment and water quality. The constraints of the problem include environmental flows for the Macquarie River (downstream of the pumping station offtake point) and stormwater schemes, a water source license for the Macquarie River and extraction limits on the groundwater bores (Table 5.8).

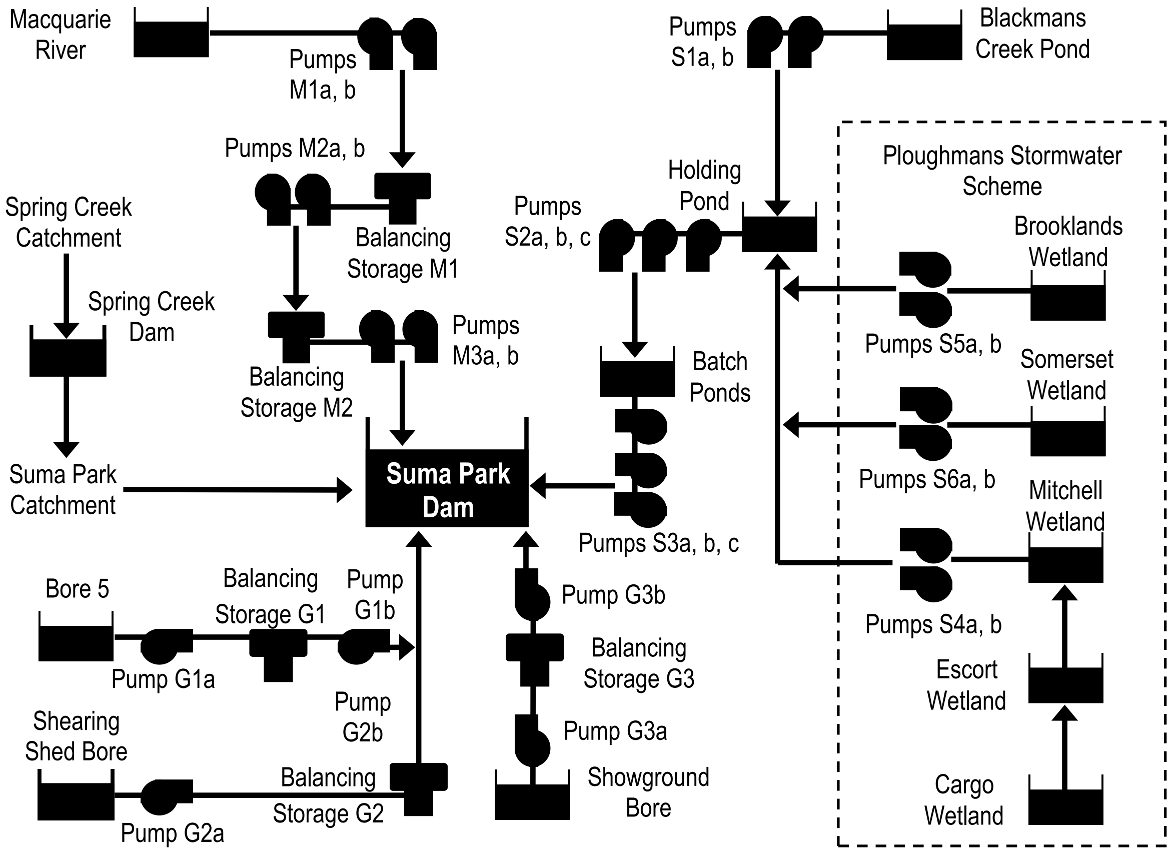


Figure 5.9: Orange Integrated Supply System process schematic – inflow to Suma Park Dam

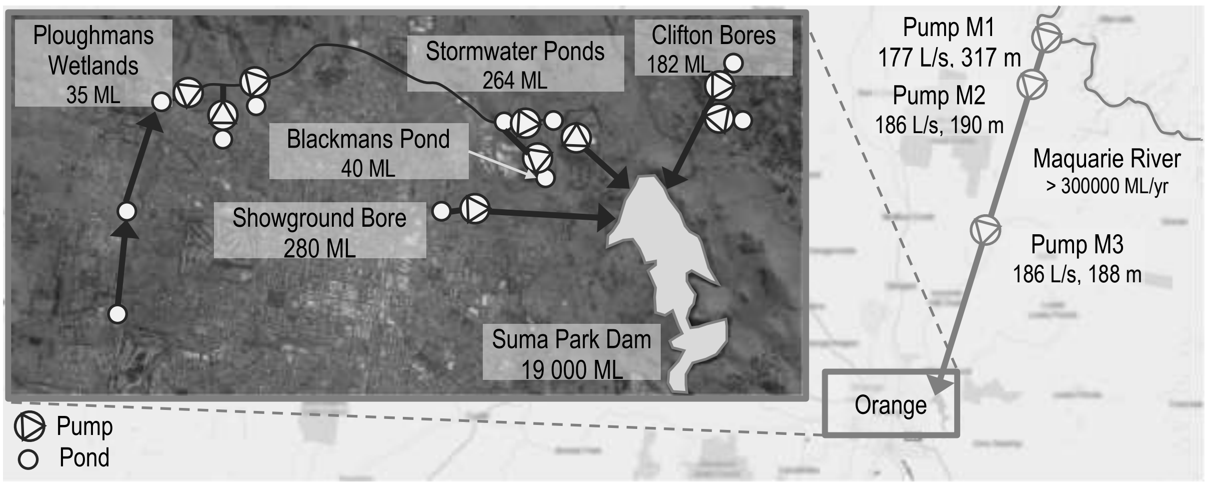


Figure 5.10: Orange Integrated Supply System layout and data

Table 5.8: Possible constraints for the Orange Integrated Supply System

Constraint	Value
Macquarie River Environmental Flow	> 108 ML/day
Blackmans' Creek Environmental Flow	> 20 ML/day
Ploughmans' Creek Environmental Flow from Pump S4	> 0.4 ML/day
Ploughmans' Creek Environmental Flow from Pump S5	> 2 ML/day
Ploughmans' Creek Environmental Flow from Pump S6	> 2 ML/day
Clifton Grove Aquifer Extraction	< 182 ML/year
Showground Aquifer Extraction	< 280 ML/year
Macquarie River Extraction License	< 12 ML/day

Energy Optimization Formulation

In this section, the developed framework is applied to the Orange Case Study to help set up the optimization procedure and identify the components and data to be modeled. Note that the model has been built taking into account all possible objectives of the system, however, the example of results presented here will focus on the minimization of energy consumption.

As all components of the system have already been constructed and considered sufficient for the operation of the system, there are no design decisions to consider, only operating decisions. For this case study, operating decisions consist of trigger levels in the various storages. These types of decision variables are chosen considering the control system available at each pump station (based on storage levels and not on time of the day) and the fact that the controls have to be defined for an operational horizon of one year or longer. As all of the pump stations have two or more pumps arranged in parallel, having different trigger level values may have a large impact on the operating point of the pumps and consequently their energy consumption. It is also likely that different trigger levels will be chosen for peak and off-peak electricity tariff periods when they are included in a cost optimization. For this system a peak/off-peak electricity tariff applies on weekdays, with weekends priced at the off-peak rate. A peak monthly electrical energy demand charge also applies to the Macquarie River pipeline pumping system. In order to assess the performance of different tank trigger levels, the infrastructure to be modeled includes the natural and urban catchments for the surface water and stormwater systems respectively, Suma Park reservoir, pipelines and pumps in the groundwater, Macquarie River and stormwater systems, and wetlands and storage ponds in the stormwater systems.

In general, the system could be modelled using hydrologic models, mass balance models, and/or hydraulic models. The choice of which model(s) will be used depends on the objectives and the processes to be modelled, on the available data and the computational times. In particular, hydrologic modeling is usually used to transform rainfall to runoff for the natural and urban catchments. For this case study, inflows inputs or approximate relationships between rain and flows were provided by previous studies by the Orange City Council. Hydraulic models are usually used for short term operations: pump energy costs can be computed accurately based on the hydraulic equations. Mass balance modeling is usually used for assessing the system in long term operations, as it can quickly compute the water available after evaporation and other losses in the system have occurred and after minimum environmental flows have been released. It cannot, however, take into account the non-linearity in the hydraulic equations and therefore assumptions need to be made in regard to the flow delivered by the pumps in the system. While hydraulic simulation would be most appropriate for the pumping stations in the system as they have multiple pumps and sometimes have connected pipelines, mass balance models would need to be used to compute the additional processes, such as evaporation and the release of minimum environmental flows that need to be taken into account given the long duration of the simulation. During an optimization process, simulating each potential solution using both a mass balance and a hydraulic model would increase considerably the computational time, particularly if data transfer between the two models was required. It is therefore suggested that the primary simulation tool should be a hydraulic solver. Rainfall-runoff modeling could be performed pre-optimization, and supplemental code added to a hydraulic model to account for functionality of a mass balance model. This would allow for consideration of the evaporation from and rainfall directly to reservoirs, changes to demands based on water restrictions and environmental flows that depend on the combined volume of two reservoirs (Spring Creek and Suma Park), infiltration losses when transferring water between reservoirs and peak power demand charges.

Another important issue to consider is what simulation time step should be used. Using a shorter time step will increase the accuracy of this hydraulic analysis and often results in feasible optimization times for storages that empty or fill in a day or two (as would likely be the case for the stormwater ponds and Macquarie pipeline balancing storages). Simulating the behavior of Suma Park dam is more challenging, however, as the variations in the water levels can have a period of several years. Thus, the computation times with a short time step become prohibitively long. A balance needs to be found between using a short enough time step for the detailed hydraulics and a long simulation time for the large storages without having a prohibitively large computational time. Given the data availability (there is 118 years of rainfall and inflow data available, with a daily time step) the time step chosen is one day.

Given that the time-step is automatically shortened by the hydraulic solver chosen (EPANET in this case), the model of the real system has been simplified in order to avoid excessive computational times. In particular, given that the levels in the balancing storages along the Macquarie pipeline vary rapidly, these storages were removed and the pipeline simulated with two parallel pumps, each representing the equivalent of the three stages of pumping (that is, the pump curves for Pumps M1a and b in Figure 5.9 were adjusted such that they represented Pumps M2a, M3a and Pumps M2b, M3b as well). This simplification is considered acceptable as the pumps in series in the Macquarie pipeline will usually be operated at the same time, given that each pump will still be controlled also by the level of Suma Park Dam. Longer computational times were also caused by the small storages after the groundwater bores. The pumps used for extraction from the aquifers (Pumps G1a, G2a and G3a in Figure 5.9) operate at relatively consistent rates, and as such they could be removed from the model and their energy use accounted for relative to the volume pumped from the second pump in each system (Pumps G1b, G2b and G3b respectively). To take into account the limited volume available from the groundwater bores, the storage tanks in the groundwater system each had a volume equivalent to a year's allocation for the respective bores. All of the stormwater pumps except for Pump S2c and Pump S3c, which are standby pumps and not in use, were included in the model. As well as the operating point of the pumps changing depending on the number of pumps used in parallel, there may be slight differences in efficiency and therefore energy use, and thus including all pumps here provided more accuracy.

All of the pumps included in the model were controlled using rule-based controls in EPANET, with conditions based on levels in one or more storages as well as time. Conditions based on downstream storages were considered as decision variables, while conditions based on upstream storages were fixed (Table 5.9). For the Macquarie pumps, there were also conditions based on the flow in the river to ensure that no water would be taken when there was not enough water available. There were four possible decision variables for each pump, a lower and upper trigger level in both the peak and off-peak time. For optimization of energy use, only two are required, as peak and off-peak tariffs are not considered. As the model was set up for other objectives including cost, which does use a peak and off-peak electricity tariff, the capability to choose different trigger levels in different periods was incorporated. A maximum of 15 pump switches per day per pump were allowed, and the end level of Suma Park Dam was constrained to

16 m (to be approximately the same as the start level). Based on license conditions, Macquarie River water can only be used when the Suma Park Dam level is below 90%, so choices for Pump M1a and M1b trigger levels in Suma Park Dam are more restricted than for other pumps.

Table 5.9: Decision variables and fixed controls for the Orange Integrated Supply System

Pump Station Action	Storage(s) Controlling Operation	Decision Variable or Fixed
Macquarie Pump M1a, M1b Off	Suma Park Dam Level High	Decision Variable
Macquarie Pump M1a, M1b On	Suma Park Dam Level Low	Decision Variable
Stormwater Pump S1a, S1b Off	Holding Pond Level High Blackmans Stormwater Pond Level Low	Decision Variable Fixed
Stormwater Pump S1a, S1b On	Holding Pond Level Low Blackmans Stormwater Pond Level High	Decision Variable Fixed
Stormwater Pump S2a, S2b Off	Batch Ponds Level High Holding Pond Level Low	Decision Variable Fixed
Stormwater Pump S2a, S2b On	Batch Ponds Level Low Holding Pond Level High	Decision Variable Fixed
Stormwater Pump S3a, S3b Off	Suma Park Dam Level High Batch Ponds Level Low	Decision Variable Fixed
Stormwater Pump S3a, S3b On	Suma Park Dam Level Low Batch Ponds Level High	Decision Variable Fixed
Stormwater Pump S4a, S4b Off	Holding Pond Level High Mitchell Wetland Level Low	Decision Variable Fixed
Stormwater Pump S4a, S4b On	Holding Pond Level Low Mitchell Wetland Level High	Decision Variable Fixed
Stormwater Pump S5a, S5b Off	Holding Pond Level High Brooklands Wetland Level Low	Decision Variable Fixed
Stormwater Pump S5a, S5b On	Holding Pond Level Low Brooklands Wetland Level High	Decision Variable Fixed
Stormwater Pump S6a, S6b Off	Holding Pond Level High Somerset Wetland Level Low	Decision Variable Fixed
Stormwater Pump S6a, S6b On	Holding Pond Level Low Somerset Wetland Level High	Decision Variable Fixed
Groundwater Pump G1 Off	Suma Park Dam Level High	Decision Variable
Groundwater Pump G1 On	Suma Park Dam Level Low	Decision Variable
Groundwater Pump G2 Off	Suma Park Dam Level High	Decision Variable
Groundwater Pump G2 On	Suma Park Dam Level Low	Decision Variable
Groundwater Pump G3 Off	Suma Park Dam Level High	Decision Variable
Groundwater Pump G3 On	Suma Park Dam Level Low	Decision Variable

Energy Optimization Results

Minimization of pump energy use over the longer term is presented here as an example of optimization of this system. Note that the system is simulated over one year, at a daily time step in EPANET. Additional computer code was added to the EPANET hydraulic simulation to take into account other process such as rainfall to and evaporation from storages. This code essentially adds a mass balance component to the hydraulic simulation. Historical rainfall for the catchments in the system was modelled in MUSIC hydrologic software to develop inflow series for the ponds and reservoirs. For this optimization the year with the closest to average rainfall was used, however, other years of rainfall were available and this optimization could be extended to consider other climate conditions.

NSGAII (Non-dominated Sorting Genetic Algorithm II) software was used for the optimization, with five random seeds, a population size of 50, 100 generations and probabilities of crossover and mutation of 0.8 and 0.02 respectively. In the best solution found, the system used a total of 793 MWh of energy over the entire year. Table 5.10 shows the volume of water pumped from each source to Suma Park Dam (and supplied from the local catchment) and the energy used by each of the pumps for the optimal solution. Pumping from the Macquarie is very energy intensive so this is only used at the very end of the simulation when the level in Suma Park Dam is very low, in order to achieve the end target level constraint (Figure 5.11 and Figure 5.12). Groundwater and stormwater sources are used initially to increase the level of Suma Park Dam to its maximum, and then not used again until around Day 160 when the level in the dam has dropped again. Only one of the Macquarie pumps is used, as, despite operating at a lower energy efficiency point, it uses less energy overall than operating two pumps in parallel. In dryer years, both pumps may need to be utilized in order to ensure supply to Suma Park Dam. Nearly all of the available groundwater license is used; G1 and G2 have a combined license of 180 ML /year, and G3 280 ML/year. Groundwater is more energy intensive than stormwater, however, it can be used at any time throughout the year, while stormwater is reliant of inflow. Most of the stormwater provided to Suma Park Dam came from the Blackman’s Creek scheme (S1) rather than the Ploughman’s Creek scheme (S4, S5 and S6). While the storage capacity of the Blackman’s Creek scheme is much lower, the pump capacity and energy efficiency is much greater than in the Ploughman’s Creek scheme, so it provides more water.

Table 5.10: Volume of water pumped/supplied and energy used in the optimal energy solution

Source	Pump	Volume (ML)	Energy (MWh)	Energy Rate (MWh/ML)
Macquarie River	M1a	0	0	0
	M1b	74	150	2.02
	Total	74	150	2.02
Groundwater*	G1	24	11	0.46
	G2	146	79	0.54
	G3	235	106	0.45
	Total	405	196	0.48
Stormwater	S1a	258	39	0.15
	S1b	479	71	0.15
	S2a	828	65	0.08
	S2b	237	21	0.09
	S3a	1022	170	0.17
	S3b	22	5.5	0.25
	S4a	178	41	0.23
	S4b	12	3.1	0.27
	S5a	24	4.8	0.20
	S5b	56	11	0.19
	S6a	60	11	0.18
	S6b	26	5.0	0.19
	Total**	1044	447	0.43
Spring Creek and Suma Park Catchment	-	3865***	-	-

*The energy consumption for the groundwater pumps includes both the transfer and bore pumps, i.e. the energy for Pump G1 includes G1a (not modelling in EPANET, energy use estimated from volume) and G1b (modelled in EPANET)

**The total volume supplied by the stormwater schemes is measured as the combined volume supplied by Pumps S3a and S3b (which discharge to Suma Park Dam), while the total energy is the total of all pumps.

***This is the volume supplied by the natural catchment for the town’s consumption, the total inflow from the catchment is greater than this however some is used to provide environmental flows and some spills.

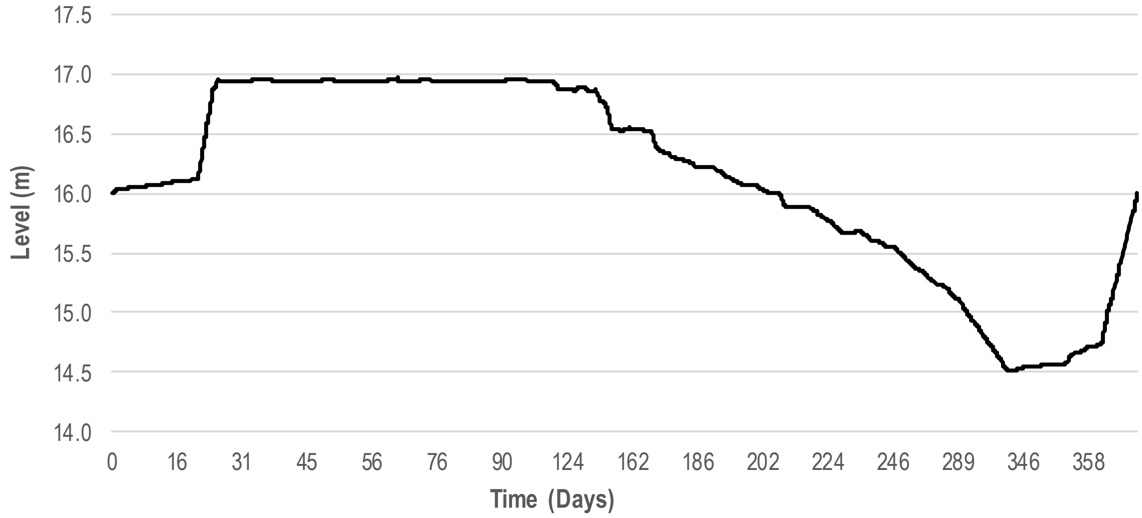


Figure 5.11: Variation in Suma Park Dam level for the energy optimal solution

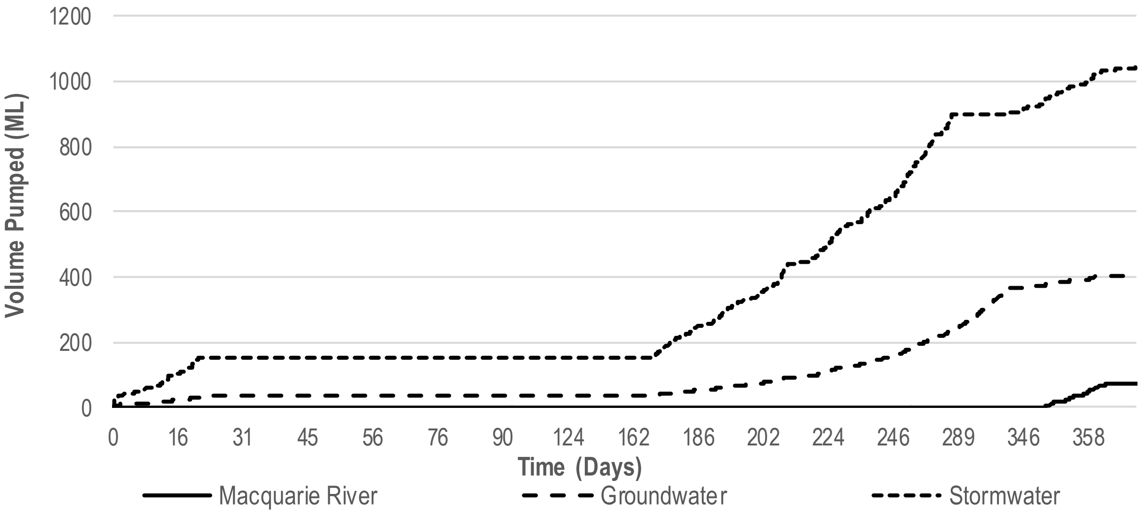


Figure 5.12: Volume pumped from each source to Suma Park Dam for the energy optimal solution

5.5 Conclusions

A generalized framework for the optimization of the design and operation of water supply and distribution systems has been developed and two case study systems have been used as examples of how to apply it. The framework is comprised of several components; the options component describes the design and operational decision variables for the optimization, the infrastructure component covers the infrastructure aspects of the system that need to be modeled and their data requirements, the analysis component includes the simulation of the system and evaluation against the objectives and constraints, and finally the government policy component describes the regulations that may affect other aspects of the framework. These components fit within an optimization algorithm structure, which firstly generates potential solutions using the decision variables in the options component, models the system according to the infrastructure component and evaluates potential solutions using the analysis component. The evaluation of potential solutions then feeds into the solution space which informs how the decision variables are changed in the next set of potential solutions. Sensitivity analysis of parameters will significant uncertainty should be undertaken to ensure robust solutions. The framework also applies to simulation of systems prior to or without optimization.

The Ridge Park MAR Scheme Case Study harvests stormwater from an urban creek and stores it in an aquifer, to be extracted at a later time and used as non-potable supply for irrigation of sporting fields and reserves. For this case study, and similar ones, the simulation of the system may be simplified by splitting the system into two parts, one for the components of the system used in winter operation (harvesting and injection) and one for the components used in summer operation (extraction and irrigation). This system highlighted the importance of simulation and analysis prior to optimization, in order to focus the formulation of the optimization problem. The Orange Integrated Supply System Case Study uses multiple water sources; natural catchment water, harvested stormwater, imported water and groundwater to supply potable demands. For this case study, finding an appropriate combination of simulation models and time step and simulation duration is important in order to provide accuracy in representing both long- and short-term operations without excessive computational times. Optimization of pump energy use for this system indicated that the groundwater and stormwater supplies are more desirable to supplement natural inflows than the imported water from the Macquarie River, which required a lot of energy to transfer water over a long distance and against a high elevation head.

The framework is generalized, and so could be applied to other water supply and distribution systems, particularly those using non-traditional water sources, to optimize their design and operation. While the framework attempts to cover all aspects of water supply in a generalized manner, it does have some limitations. Along with the supply of water, there will always be a need to manage wastewater. Apart from considering recycled wastewater as a source, this framework does not cover wastewater systems in terms of collection, transport, treatment and potential discharge of wastewater into the environment. Treatment of raw water supplies is included in the framework, however, the details of such treatment and measurement of water quality throughout a water distribution system are not focused on as much as the design and operation of the systems. A difficulty of applying this framework will be the definition of the boundary of a system and which aspects should be analyzed. Currently, there does not exist commercial software that has all of the capabilities considered in the framework (i.e. both hydrologic and hydraulic simulation). This means that specialist simulation models may need to be developed for particular systems (as was done for the second case study). Future developments in simulation software may reduce the difficultly of combining hydrologic, mass balance and hydraulic considerations and remove the need for specialist tools built for individual systems. In the future, the framework should be tested with other case study systems to fully investigate its benefits.

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References

References are included in Chapter 8. In addition, the final published paper in Appendix B has the references listed.

Chapter 6 Optimization of Pumping Costs and Harvested Volume for a Stormwater Harvesting System

Publication 3

Blinco, L.J., Simpson, A.R., Lambert, M.F., and Marchi, A.

School of Civil, Environmental and Mining Engineering

The University of Adelaide, Adelaide, SA 5005 Australia

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Although the manuscript has been reformatted in accordance with University guidelines, sections have been renumbered for inclusion within this thesis, details of references have been updated where applicable, and some changes have been made based on the examination of this thesis, the paper is otherwise presented herein as submitted.

Primary Author	Blinco, L.J. (Candidate)
Contribution	Development and implementation of methodology, design of experiments, interpretation and analysis of results, preparation of manuscript and acting as corresponding author.
Overall Percentage	80%

This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper and I hereby cerfity that the statement of contribution is accurate.

Signed:...... .... Date:......9/11/17..

Co-Authors

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate to include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Co-Author	Simpson, A.R.
Contribution	Research supervision and manuscript evaluation.

Signed:. .... Date:....9/11/2017.......................

Co-Author	Lambert, M.F.
Contribution	Research supervision and manuscript evaluation.

Signed:.... .... Date:.......9/11/17.................................

Co-Author	Marchi, A.
Contribution	Research supervision and manuscript evaluation.

Signed:...... .... Date:....9/11/17...............................

Abstract

A harvested stormwater and managed aquifer recharge system has been analysed through both simulation sensitivity analysis and optimization to reduce operational pumping costs and increase the volume of water harvested. The simulation sensitivity analysis explored increasing the size of a storage tank, replacing the three harvesting pumps and using wider tank trigger levels in the system operation. In the optimization, trigger levels and irrigation schedules were considered as decision variables. Various streamflow (input) series have been considered in the optimization by finding the optimal controls for each individual series or by finding the controls that best perform under a range of different conditions. Optimal controls for the current system were compared to those found for the system with new replacement pumps. The newly sized pumps were found to provide significant benefits by reducing pump operating costs by 50%, and by increasing the volume of water able to be harvested. Using wider tank trigger levels and altering the irrigation schedule so that the irrigation pump operated at a more efficient point also resulted in a small reduction in cost for the current system.

6.1 Introduction

As climate change and population growth highlight water security issues, alternative water sources are increasingly being used to supplement potable supply (Fielding et al. 2015). Harvested stormwater is an example of such a source, in which runoff from pervious and impervious surfaces (generally in urban environments) is collected, treated and supplied to consumers (Naylor et al. 2012). Typically, stormwater is supplied for non-potable end uses such as irrigation of public spaces, household garden watering or toilet flushing, however, in some cases it has been used for potable supply (McArdle et al. 2011). As well as improving water security, harvested stormwater can have other benefits that communities place value on such as reduced flooding, improved surface water quality, improved hydrologic function and improved aquatic habitats (Londoño Cadavid and Ando 2013). Where there is low understanding of the risks of stormwater to human health, communities may be less likely to accept harvested stormwater projects and education programs may need to be considered (Hwang et al. 2006). Water system managers perceive operation and maintenance costs as one of the greatest barriers to implementation of harvested stormwater projects (Dobbie and Brown 2012). Determining strategies to reduce ongoing energy costs of these systems is therefore an important task.

Previous studies on the optimization of harvested stormwater systems have usually considered only the design of the system, not the operation. When harvested stormwater is used to supplement or add to potable supplies, the yield of the system (volume of water harvested or provided to users) is an important variable to be maximized (such as in McArdle et al. 2011; Marchi et al. 2016a; di Matteo et al. 2016). McArdle et al. (2011) optimized the design of a harvested stormwater system to minimize life-cycle costs, maximize yield and minimize the impact of the system on the amenity of a public reserve. Marchi et al. (2016a) also optimized the design of a harvested stormwater system, which included Managed Aquifer Recharge (MAR). They included consideration of externalities and climate change, and found that the values of both the net present value and yield objectives decreased when climate change impacts were considered.

As well as objectives of minimizing costs and maximizing yield, maximizing water quality is often included, such as in di Matteo et al. (2016). Studies assessing the performance of harvested stormwater systems often focus on water quality rather than the cost of energy for pumping (for example, Burns and Mitchell 2008; Nnadi et al. 2015; Petterson et al. 2016). Labadie et al. (2012) optimized the operation of a stormwater system, however, the objective was to reduce the environmental impact on the downstream ecosystem rather than minimization of pumping costs or maximization of the volume of water harvested.

The remainder of this chapter is organized as follows; firstly, background on a case study system gives context for the other sections, the methodology of the analysis and optimization of this case study is then discussed, followed by results of the simulation sensitivity analysis and optimization, and finally conclusions are drawn.

6.2 Case Study: Ridge Park Managed Aquifer Recharge System

The Ridge Park Managed Aquifer Recharge Scheme in South Australia supplies non-potable water to sports and recreational areas for irrigation use. South Australia has largely seasonal rainfall, with most occurring over the winter months around May to October. Water supplies also rely on imported water from the River Murray, which is costly (due to distance and elevation rise) and highly regulated. Alternative water source systems are important to reduce use of potable supplies from variable catchment inflows and the River Murray. The system is located in the metropolitan area of the city of Adelaide and is operated by the Unley City Council. It was designed to harvest up to 60 ML of stormwater per year for injection into a confined aquifer, which occurs over the winter, while in summer the harvested water is drawn from the aquifer and used for irrigation. Figure 6.1 shows a schematic of the system, which is described below. Note that the case study analyzed in this research was based on the best available information for the real-life system. There may be some differences between the simulated and real-life systems.

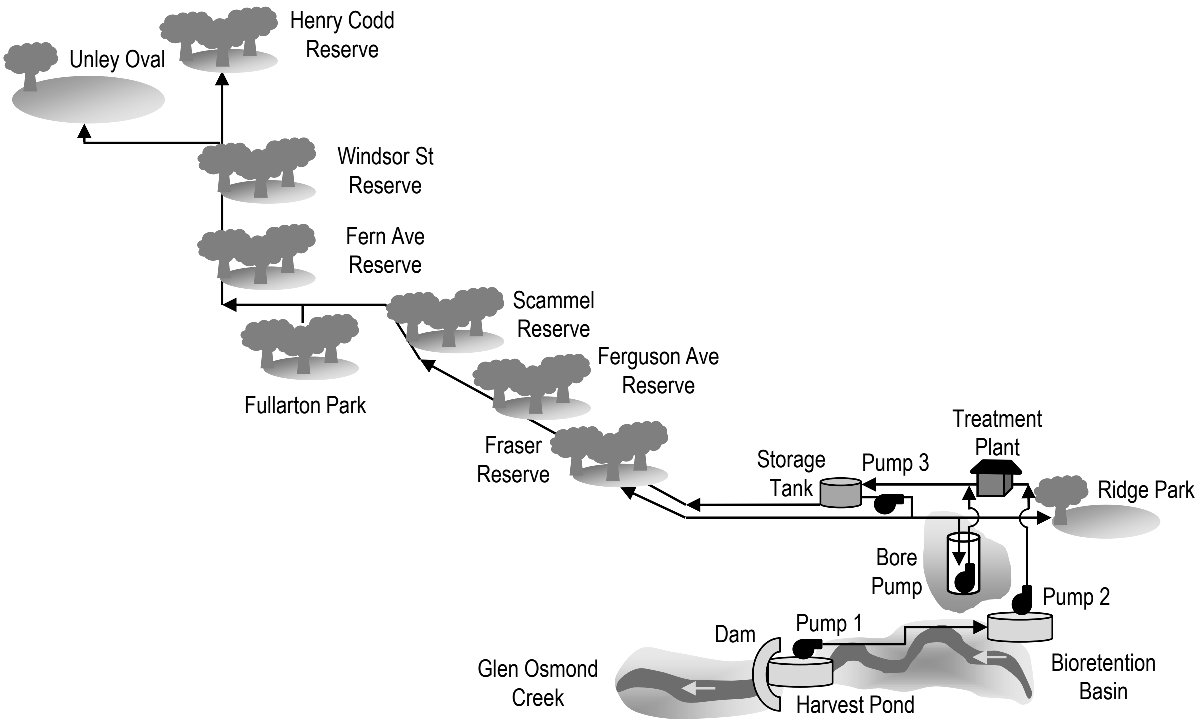

Figure 6.1: Schematic of Ridge Park Managed Aquifer Recharge Scheme

In winter, stormwater is harvested from the Glen Osmond Creek, an urban waterway that receives approximately 200 ML of runoff per year (on average) at the point of harvest. A dam has been constructed in Ridge Park, in the suburb of Myrtle Bank, to create the 1500 kL Harvest Pond. Water is then pumped to a Bioretention Basin which provides some treatment, and then pumped to a small treatment plant that includes a micro-filter and ultra-violet (UV) treatment. Once the water has been adequately treated, it is stored in a 36 kL above ground tank next to the treatment plant and final pump station. From the Storage Tank, water is injected into an artesian, fractured rock aquifer for long term storage.

In summer, when no water is being harvested, water is extracted from the aquifer using the same bore and stored in the tank, before being pumped or gravity-fed to irrigation points. The Ridge Park Reserve is irrigated by a pressurized 90 mm diameter irrigation line, as it is at higher elevation than the Storage Tank. Fraser Reserve is also connected to the pressurized system; although it is at lower elevation, it is not enough to ensure adequate pressures for irrigation. In total, the pressurized system supplies almost 15 ML per year for irrigation. The remaining seven open space reserves are on a 180 mm diameter gravity-fed line which supplies a total demand of over 37 ML per year. The total irrigation pipeline length is 4.3 km. As rainfall and therefore streamflow is variable year to year, the volume harvested will also vary. On average the harvested volume should be enough to provide the irrigation demand for the grassed reserves, however, the injection volume is not restricted to the harvest volume from the previous season. If not enough stormwater was harvested over several winter seasons, potable back-up supply is available (assuming no water restrictions are in place).

6.3 Methodology

The framework presented in Blinco et al. (2017a) has been used to develop the methodology for this study. Within an optimization algorithm, the framework incorporates the options (decision variables) for the problem, the water and electricity infrastructure that may need to be modelled, the simulation tools used to model the system and the analysis of the system in terms of objectives and constraints. Blinco et al. (2017a) also discuss the importance of sensitivity analysis; as well as finding optimization results that are robust for different inputs, this process can highlight parameters that are important to, or in contrast, have little impact on, the results of an optimization problem.

In this research, sensitivity analysis is performed prior to optimization for a range of system configurations and inputs, by simulating the system in EPANET hydraulic simulation software (Rossman 2000). Performing simulation runs is an extremely important part of the process so that the user can fully understand the system prior to the investigation of optimization. Results from the simulation sensitivity analysis are then compared in their absolute form (such as cost or number of pump switches) and relative to the base case (current operation) as a percentage. These simulation results inform what is investigated through optimization of the system; the solution space for the optimization may also be reduced by removing options that had little impact in the simulation sensitivity analysis.

6.3.1 Simulation Model Development

Two models of the case study system have been developed in EPANET; one for the winter operation of harvesting and confined aquifer injection, and one for the summer operation of confined aquifer extraction and irrigation. The operation of the bore cannot be switched from injection to extraction frequently, so the system is operated (and hence modelled) with two distinct seasons. For both models, assumptions included that minor losses are negligible, the pump and efficiency curves from the manufacturer catalogue are still valid, and there has been no build-up of biofilm in the pipe systems. These models did not simulate water quality as the main focus of this study is operational pumping costs. Both systems were simulated for one week in EPANET, with a 15 minute hydraulic time step. The simulation time was representative of the full season as multiple streamflow scenarios were considered in the winter system and the irrigation schedule repeats weekly in the summer. Each year the specific start and end of each season will vary depending on the weather, however it is assumed that each season lasts for 26 weeks.

Trigger levels (related to volumes in the three storages as shown in Table 6.1) control when the pumps in the winter harvesting and injection system (Pumps 1, 2 and 3) turn on and off. During summer, the Bore Pump is also controlled by trigger levels in the Storage Tank, while Pump 3 is controlled by the irrigation demands instead of trigger levels. The irrigation schedule is arranged so that different open space reserves are irrigated on different nights (Table 6.2 and Figure 6.2). Pump 3 is a variable speed pump (VSP) and is operated at 80% of full speed for injection (such that the flow is less than the 7 L/s maximum for injection) and 75% of full speed for irrigation (such that the target pressure downstream of the pump is achieved at the expected demand rates). A peak/off-peak electrical energy price tariff applied to the entire system; a peak price of 25.53 c/kWh was applied from 7am to 9pm on weekdays, and an off-peak price of 15.26 c/kWh was applied over night and on weekends. The electricity tariff pattern assumed the simulation was starting on a Sunday. Blinco et al. (2017a) gives a detailed description of the development of the simulation models.

Table 6.1: Trigger Levels for the Ridge Park system

Storage and Trigger Level Type	Current Setpoint		Start Pump	Stop Pump
	Volume (%)	Level (m)		
Harvest Pond High Level	80	1.6	1	-
Harvest Pond Low Level	50	1.0	-	1
Bioretention Basin High Level	90	0.80	2	1
Bioretention Basin Low Level	50	0.59	-	2
Storage Tank High Level	90	2.25	3	2, Bore
Storage Tank Low Level	70	1.75	Bore	3

Note that this table has been taken from Blinco et al. (2017a) and provided here for completeness.

Table 6.2: Irrigation demand schedule for the Ridge Park system

Open Space Reserve	Demand Rate (L/s)	Duration/day (hr)	Start Time	Irrigation Days
Ridge Park 1	3.53	8.33	9:30 PM	Mon & Wed
Ridge Park 2	3.53	8.67	9:30 PM	Tues & Thurs
Fraser Reserve	1.41	5.83	9:30 PM	Mon & Wed
Ferguson Ave Reserve	2.00	5.00	9:30 PM	Tues & Thurs
Scammell Reserve	2.15	6.00	10:00 PM	Tues & Thurs
Fullarton Park 1	3.85	1.67	10:00 PM	Mon & Wed
Fullarton Park 2	3.85	6.67	10:00 PM	Tues & Thurs
Fern Ave Reserve	3.53	3.33	10:00 PM	Mon & Wed
Windsor St Reserve	2.20	8.00	8:30 PM	Tues & Thurs
Henry Codd Reserve	1.10	8.00	10:00 PM	Mon & Wed
Unley Oval	5.57	9.00	9:00 PM	Sun, Mon & Wed

Note that this table has been taken from Blinco et al. (2017a) and provided here for completeness.

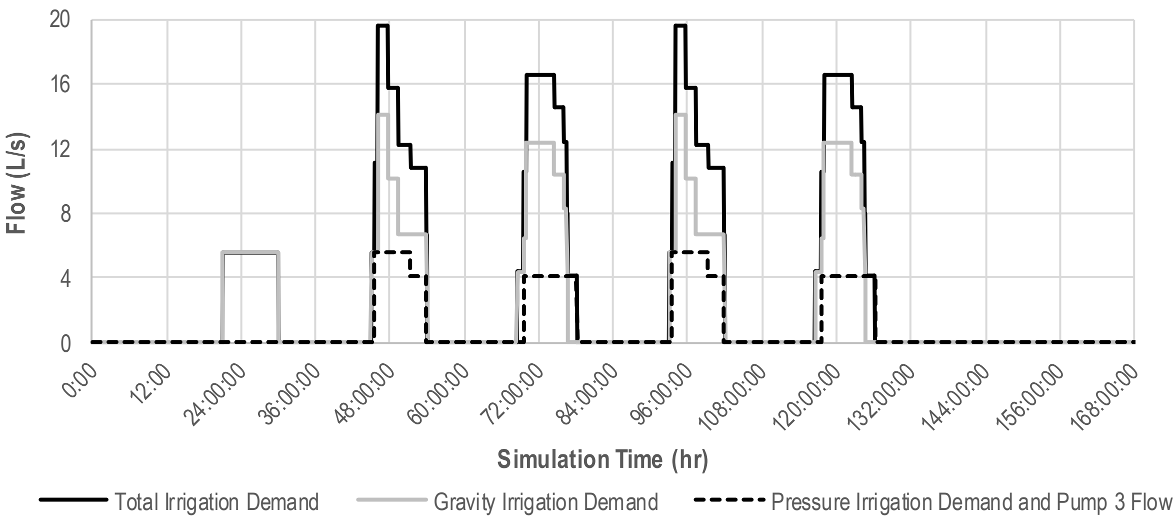

Figure 6.2: Irrigation schedules under the current operation (note that this figure has been taken from Blinco et al. (2017a) for comparison to Figure 6.10)

<u>Winter System (Stormwater Harvesting and Confined Aquifer Injection)</u>

The winter simulation model within EPANET included the Harvest Pond, Biorentention Basin, Storage Tank and Aquifer, and all the pumps and pipes required to transfer water between them (Figure 6.3). Glen Osmond Creek was included as an input node, with a negative base demand applied to simulate in EPANET that water should flow into the Harvest Pond. Recorded streamflow data were applied as a demand pattern to this node. A volume-elevation curve was applied to the Bioretention Basin to account for the porosity of the filter media and the height of water storage above this. No volume curve information was available for the Harvest Pond, so it was assumed to have a constant surface area.

Pressure sustaining valves (PSVs) were inserted into the simulation model to take into account the fact that the discharges to the Bioretention Basin and Storage Tank are from pipes over the top of these storages. A general purpose valve (GPV) upstream of the Storage Tank took into account the energy losses through the micro-filter (losses over the UV machine are assumed negligible). A pressure breaker valve was used to take into account the headloss through the bore during injection. The minimum head loss over the bore was 3.0 m due to the water being injected around the Bore Pump. This head loss increased to 4.8 m over the course of 1 week (0.3 m increase per day) as the bore starts to clog (it was assumed that a backwash of the bore is initiated once a week). The effective water level of the confined aquifer was estimated to be 5.0 m above the ground surface at the bore pit and the impressed level during injection another 45.0 m above this.

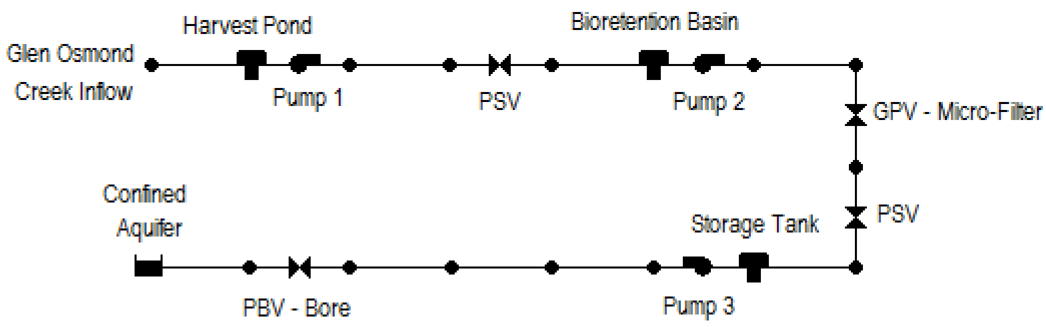

Figure 6.3: EPANET model of the Winter System (harvesting and confined aquifer injection)

<u>Summer System (Confined Aquifer Extraction and Irrigation)</u>

The summer simulation model within EPANET included the Aquifer and Bore Pump, Storage Tank, Pump 3 (for irrigation) and the pressure and gravity distribution systems (Figure 6.4). At each open space reserve, there are small irrigation systems transferring water from the main distribution line to the sprinkler heads. These pipes were not included in the EPANET model, as the demand information available was for each open space reserve rather than individual sprinklers, and pressure constraints were considered just downstream of Pump 3 to ensure there was enough pressure for the sprinklers to operate effectively. Demands at Ridge Park and Fullarton Park were split into two groups of irrigation stations so that the irrigation for these areas can be spread out over different nights. As in the winter model, there was a PSV just upstream of the Storage Tank to account for the inlet being at the top of the tank. There was also a PSV in the bore headworks which represented an existing valve. The confined aquifer was modelled as a reservoir, with the head level assumed to be at the effective water level for extraction. The Bore Pump was not likely to be operated for long enough to create significant drawdown (Wang et al. 2009).

6.3.2 Optimization Model Formulation

The Non-dominated Sorting Genetic Algorithm II (NSGA-II, Deb et al. 2002) was chosen as it can incorporate multiple objectives and has been shown to perform well for water distribution system problems (Wang et al. 2015). NSGA-II was connected with the EPANET Toolkit To Alter Rule-based controls (ETTAR) developed in Marchi et al. (2016b) to allow the optimization of the operating rules (trigger levels and irrigation scheduling) for the case study system. ETTAR also incorporates the variable speed pump (VSP) efficiency correction to allow for accurate calculation of pump energy use for VSPs (Marchi and Simpson 2013). Simulation sensitivity analysis was performed prior to optimization, in order to provide a better understanding of the system and refine the optimization formulation. Objectives and decision variables are introduced here, and further developed after the results of the sensitivity simulation analysis are presented.

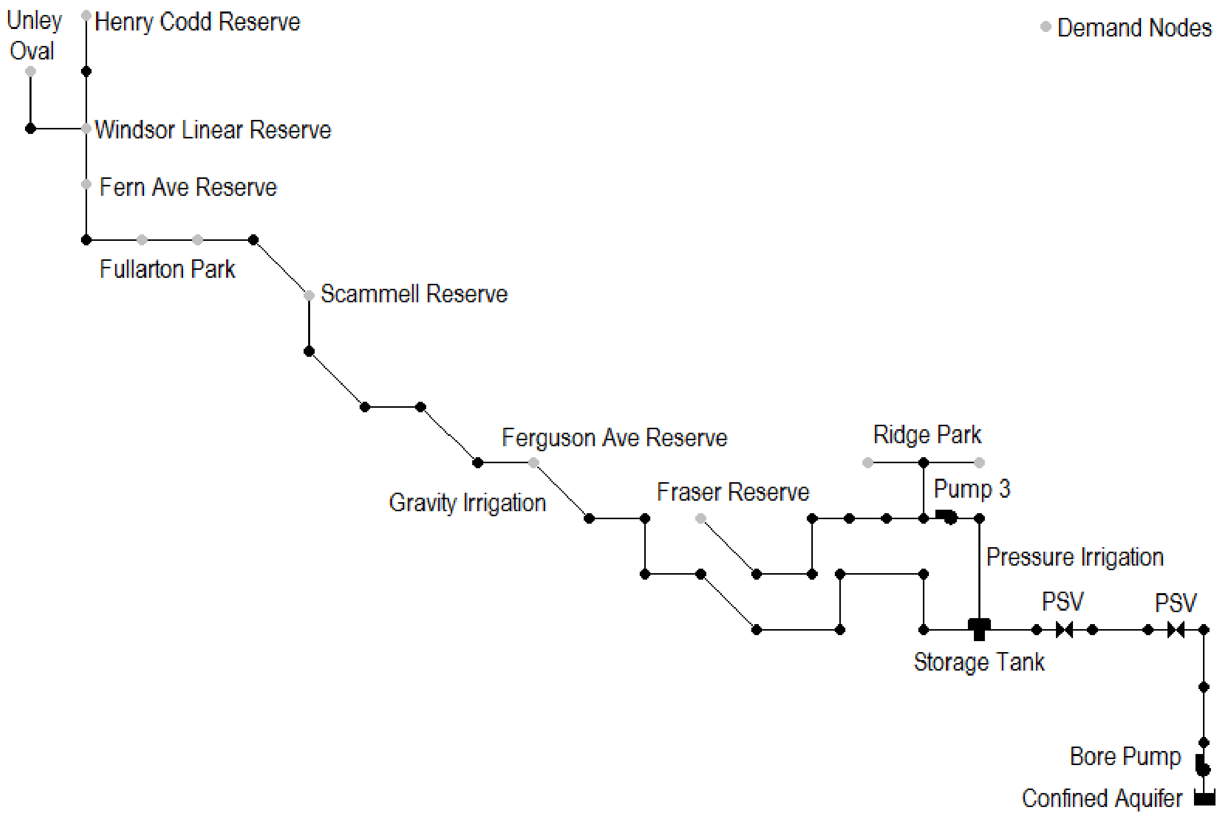

Figure 6.4: EPANET model of the Summer System (confined aquifer extraction and irrigation)

There were two objectives of the optimization problem; firstly to minimize the cost of electricity used to operate the pumps (Eq. 6.1) and secondly maximize the volume of water harvested over the simulation period (Eq. 6.2). In many water resources optimization problems, objective functions for operational cost take into account the volume of water delivered, calculating the cost per unit volume pumped. In this case, however, the volume harvested is considered as an additional objective function to be maximised, and therefore does not need to be included in the cost objective function.

$$OC = \sum_i T_i x E_i \tag{6.1}$$

$$VH = \sum_i V_i \tag{6.2}$$

where OC = operational cost (dollars/week); T_i = electricity tariff for each time step i (dollars/kWh); E_i = energy consumption for each time step i (kWh); VH = volume harvested (ML); and V_i = volume harvested in each time step i (ML). The time step i would range from 1 to 672 for the week long simulation at 15 minute time increments used for the case study in this research.

Both operational and design decision variables were considered in this paper. Although the case study system considered in this research had already been constructed, adjustments to the design were possible, including upgrading the storage tank size and replacing the pumps. Operational decision variables were in the form of trigger levels in each of the storages that would control the pump operations. The irrigation schedule was also considered as a decision variable, which required new computer code to be developed to implement this in NSGA-II. For each open space reserve, two decision variables and four set variables were defined. The decision variables were the start day for irrigation (coded as integers with 0 being the starting day for the simulation) and the start time for irrigation (also integer coded, referring to the time in hours, i.e. 8:30pm would be 20.50 for the simulation). For each open space reserve, the demand rate (in L/s), duration of irrigation (in hours), number of days of irrigation (per week) and the gap between irrigation days (a gap of one day results in irrigation every second day) were set.

As upgrades to the system infrastructure come at a cost, Net Present Value (NPV) analysis can be used to determine if operational cost savings achieved with new infrastructure would provide a net financial benefit. NPV analysis takes into account the costs and returns of a project over time, with future costs and benefits discounted to current prices, as shown in Eq. (6.3). The operational costs savings realised by any new infrastructure were treated as returns into the future, and the capital costs of new infrastructure were assumed to occur at the start of the period and therefore were not discounted. A positive NPV indicates that a project is financially beneficial, while a negative NPV indicates that it has a net financial cost.

$$NPV = \sum_{t=1}^{T} \frac{C_O}{(1+r)^t} - C_c \tag{6.3}$$

where NPV = net present value (dollars); T = time period (years); t = time step (years); C_O = operating cost returns for one time step (dollars/time step) (in this study the difference in the operating cost with new infrastructure and the operating cost with current infrastructure); r = discount rate (decimal); and C_c = capital cost of new infrastructure (dollars).

Two different methods for incorporating different streamflow series were also implemented in the optimization (Figure 6.5); (1) individual series and (2) looped series. The first considers each streamflow series individually, which would be most applicable in situations where a good forecast is available and the operating rules can be easily altered. Optimization of the system is performed with one streamflow series used in the simulation, if other streamflow series are of interest, the optimization is repeated for each new series. In this method, if n series are considered, n Pareto fronts will be produced. The second method loops the streamflow series within the optimization algorithm, generating solutions that will be robust to many possible realizations. Each potential solution in the optimization is simulated n times for n streamflow series, however, only one Pareto front is produced. The objective function values calculated for each of the n simulations of one potential solution are averaged to provide just one value of each objective function for each solution.

6.4 Simulation Sensitivity Analysis

6.4.1 Simulation Sensitivity Analysis Scenarios

Simulation of the current operation of the system in Blinco et al. (2017a) showed that the pumps were turning on and off very frequently, which should be avoided to reduce maintenance costs and prevent general wear and tear of the pumps. One of the problems was that Pumps 1 and 2 are oversized compared to Pump 3 (the flow into the aquifer is restricted to 7 L/s, however, Pumps 1 and 2 operate at above 20 L/s). The operation of the system with the current pump curves was compared to that with newly sized pump curves for Pumps 1 and 2 that will allow them to operate at around 7 L/s. The new pump curve for Pump 2 was also chosen to significantly improve the efficiency of this pump. Sizing of Pump 3 was considered; as it was originally designed to supply two bores, the best efficiency occurs closer to 14 L/s than 7 L/s. A new pump was sized to achieve an operating point that had lower flow (at full speed) and is closer to the best efficiency point. Sizing of the Bore Pump was not considered, as while the head range of the current pump was higher than needed for extraction, it is also used to backwash the bore when injecting, which may have a significantly higher head requirement.

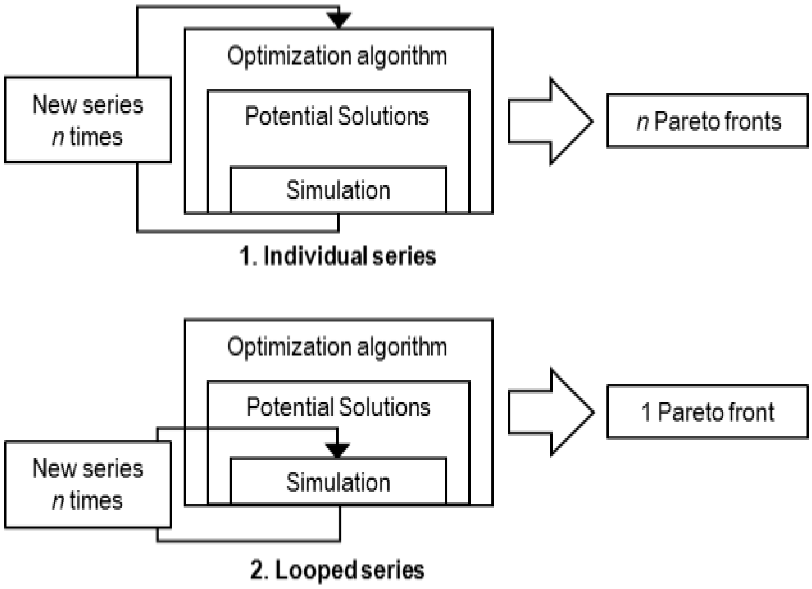

Figure 6.5: Methods for incorporating streamflow series in optimization

Another contributing factor to the frequent pump switches was that the trigger levels controlling the pumps are close together, and the storages (particularly the Storage Tank) are small. Two sets of trigger levels were investigated; (1) the current trigger levels (shown in Table 6.1) that only used the top half of the Harvest Pond and Bioretention Basin, and only 20% of the volume of the Storage Tank, and (2) wider trigger levels that used 70% of each storage volume (Table 6.3). Increasing the size of the Storage Tank was also investigated: the current Storage Tank volume of 36 kL was compared to double, five times and ten times the size of the existing tank.

Table 6.3: Wider trigger levels used in the simulation sensitivity analysis

Storage and Trigger Level Type	Setpoint		Start Pump	Stop Pump
	Volume (%)	Level (m)		
Harvest Pond High Level	90	1.8	1	-
Harvest Pond Low Level	20	0.4	-	1
Bioretention Basin High Level	90	0.80	2	1
Bioretention Basin Low Level	20	0.26	-	2
Storage Tank High Level	90	2.25	3	2, Bore
Storage Tank Low Level	20	0.50	Bore	3

A total of 20 different simulation sensitivity analysis scenarios (Table 6.4) were considered for the winter system (harvesting and confined aquifer injection), with different combinations of current or wide trigger levels, current or new pumps, and Storage Tank sizes. Scenario A used the current values for the following – trigger levels, pump curves and tank sizes – therefore results from this scenario were considered to be the baseline for comparing all other scenarios. The summer system (confined aquifer extraction and irrigation) was simulated with the newly sized Pump 3, a larger tank and wider trigger levels for the Bore Pump.

Each scenario was simulated six times with six different week-long streamflow series. The streamflow series selected represented a range of operating conditions (dry, wet or average week and (relatively) constant or variable flow) (Figure 6.6). Results of the current operation indicated that when the average flow was above approximately 25 L/s, the injected volume could not be significantly increased. In the analysis of current operations in Blinco et al. (2017a), it was found that when the average streamflow was above 25 L/s, there was not a significant increase in the amount of water able to be harvested due to restrictions of storage volumes and pump flow rates. Of the six streamflow series selected for simulation sensitivity analysis, four had average flows lower than 25 L/s to provide a wider range of results and two had average flows around 25 L/s with different levels of variability. None of the series used in the simulation sensitivity analysis had average flows significantly greater than 25 L/s.

Table 6.4: Simulation sensitivity analysis scenarios for the Winter System

Scenario	Trigger Levels[2]		Pumps[3]		Storage Tank Size			
	Current	Wide	Current	New	36 kL	72 kL	180 kL	360 kL
	HP 50-80% BB 50-90% ST 70-90%	HP: 20-90% BB: 20-90% ST: 20-90%	Q_1: 20 L/s Q_2: 25 L/s Q_3: 7 L/s	Q_1: 7 L/s Q_2: 7 L/s Q_3: 7 L/s	Current			
A_{winter}	X		X		X			
B_{winter}		X	X		X			
C_{winter}	X			X	X			
D_{winter}[1]		X		X	X			
E_{winter}	X		X			X		
F_{winter}		X	X			X		
G_{winter}	X			X		X		
H_{winter}		X		X		X		
J_{winter}	X		X				X	
K_{winter}		X	X				X	
L_{winter}	X			X			X	
M_{winter}		X		X			X	
N_{winter}	X		X					X
P_{winter}		X	X					X
Q_{winter}	X			X				X
R_{winter}		X		X				X
S_{winter}	X		3[4]	1, 2	X			
T_{winter}		X	3	1, 2	X			
U_{winter}	X		3	1, 2		X		
V_{winter}		X	3	1, 2		X		

[1]Boxed items correspond to scenarios with the 'best values' in Table 6.5.
[2]Trigger levels for the Harvest Pond (HP), Bioretention Basin (BB) and Storage Tank (ST).
[3]Typical pump operating flow rates for the current and new pump models.
[4]In Scenarios S_{winter} – V_{winter}, new pump models were considered for Pumps 1 and 2 only, with the current model used for Pump 3.

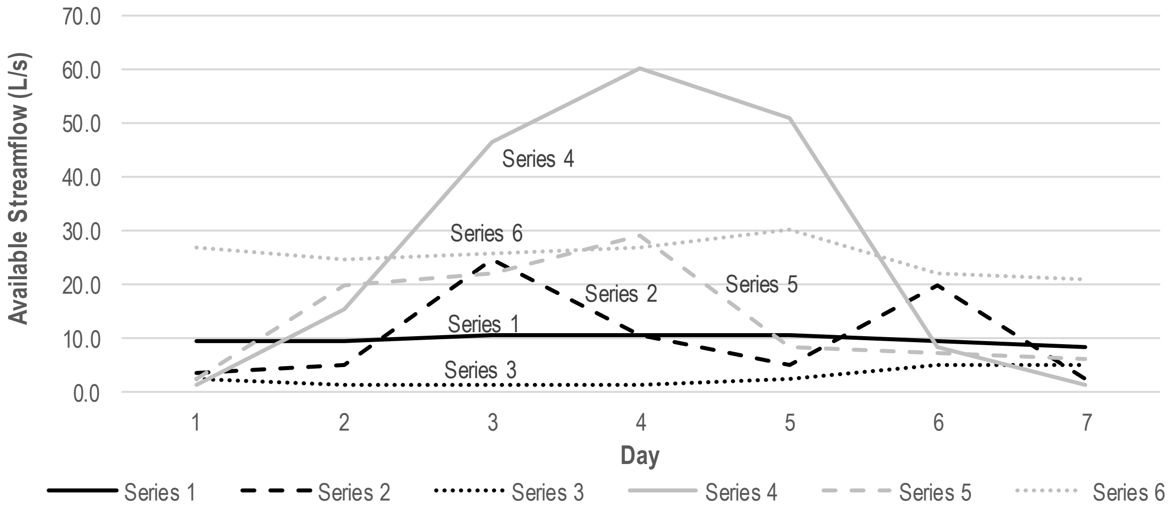

Figure 6.6: Streamflow series used in the simulation sensitivity analysis

6.4.2 Simulation Sensitivity Analysis Results – Winter System (Stormwater Harvesting and Confined Aquifer Injection)

For each simulation, the cost of pumping, volume pumped into the confined aquifer and number of pump switches were calculated. The results for each scenario were then averaged over the different streamflow series (Table 6.5 and Table 6.6) and the results for each streamflow series were averaged over the different scenarios (Table 6.7). Where the volume harvested is below 2.0 ML per week and therefore below 52 ML (the total irrigation volume) in the season (26 weeks), additional water from the aquifer may be drawn over the summer period depending on the extraction and injection levels in the previous year. Potable back-up supply can also be used if required.

Simulation Results for Changes in Trigger Levels, Pump and Storage Volumes

Table 6.5 shows the cost rate (in c/kL) for each pump and overall, the total cost over a week of operation, the total volume of stormwater injected to the confined aquifer over a week of operation, and the number of pump switches per day for each. The highlighted cells show the 'best' value for each result variable (for most of the variables this is the minimum, however, for the volume injected it is the maximum). In all scenarios, the operation of the new pumps was less expensive than the current pumps, with cost rates around 4-5 c/kL of water injected compared to 8-9 c/kL of water injected. The overall and individual pump cost rates were lowest in Scenario M_{winter}, which used the wider trigger levels and the second largest tank size as well as the new pumps. Scenario M_{winter} also had the best cost rate overall and for Pump 3. In terms of total cost per week, Scenario D_{winter} was the least expensive, however, this was partly due to a reduced volume of stormwater injected. Incorporating all possible changes to the system – the wider trigger levels, the new pumps and the largest Storage Tank size in Scenario R_{winter} gave the best results in terms of the volume of stormwater injected and number of pump switches. There were slight differences in the scenarios that resulted in the best values across the streamflow series, however, the overall trends were very similar.

Table 6.5: Comparison of simulation results for changes in trigger levels, pump sizes and storage volumes

Scenario	What has been changed? Trigger Levels	Pumps	Storage Tank	Cost (c/kL) Pump 1	Pump 2	Pump 3	Total[3]	Cost ($/wk)	Volume (ML/wk)	Pump Switches (/day) Pump 1,2,3
A_{winter}			36 kL[2]	0.677	2.244	5.780	8.849	219	2.50	74,79,3
B_{winter}	Wide		36 kL	0.663	2.212	5.921	8.804	209	2.42	70,69,1
C_{winter}		New	36 kL	0.390	0.453	3.643	4.503	143	3.16	54,49,4
D_{winter}[1]	Wide	New	36 kL	0.381	0.447	3.568	4.408	138	3.11	47,43,1
E_{winter}			72 kL	0.665	2.252	5.795	8.717	216	2.49	78,74,2
F_{winter}	Wide		72 kL	0.657	2.273	5.916	8.853	212	2.44	72,67,0
G_{winter}		New	72 kL	0.389	0.454	3.633	4.492	143	3.17	53,47,2
H_{winter}	Wide	New	72 kL	0.379	0.445	3.528	4.360	141	3.26	46,42,1
J_{winter}			180 kL	0.665	2.278	5.810	8.693	215	2.49	75,67,1
K_{winter}	Wide		180 kL	0.656	2.251	5.797	8.736	214	2.48	70,63,0
L_{winter}		New	180 kL	0.390	0.453	3.630	4.490	144	3.20	48,46,1
M_{winter}	Wide	New	180 kL	0.368	0.426	3.379	4.187	145	3.38	40,38,0
N_{winter}			360 kL	0.661	2.289	5.061	8.774	215	2.48	75,68,1
P_{winter}	Wide		360 kL	0.658	2.273	5.622	8.603	217	2.54	67,61,0
Q_{winter}		New	360 kL	0.391	0.459	3.662	4.537	143	3.17	49,44,1
R_{winter}	Wide	New	360 kL	0.374	0.432	3.421	4.233	152	3.51	34,32,0
S_{winter}		1, 2[4]	36 kL	0.392	0.455	5.810	6.674	163	2.46	104,109,3
T_{winter}	Wide	1, 2	36 kL	0.387	0.451	5.857	6.702	159	2.41	99,105,1
U_{winter}		1, 2	72 kL	0.393	0.455	5.810	6.670	163	2.46	101,109,2
V_{winter}	Wide	1, 2	72 kL	0.385	0.445	5.707	6.546	159	2.44	93,100,0

[1]Boxed cells represent the 'best values' for each variable, scenarios that resulted in these 'best values' are boxed here and in Table 6.4 and Table 6.6.

[2]Current Storage Tank size is 36 kL.

[3]The total cost rate is calculated as the average of the individual cost rates for each streamflow series, rather than the average cost per week divided by the average volume per week.

[4]In Scenarios S_{winter} – V_{winter}, new pump models were considered for Pumps 1 and 2 only, with the current model used for Pump 3.

Comparison of Simulation Results to Scenario A_{winter} as Baseline Case

Using Scenario A_{winter} as a baseline (Table 6.6) shows that replacing the pumps has the most significant impact on cost, while the other changes result in only minor cost reductions. The new pumps also have the most significant impact on reducing the number of pump switches, however, using wider trigger levels and increasing the Storage Tank size (to five or ten times the current size) does also have some effect. Doubling the Storage Tank size does not have a significant impact on either cost or pump switches. The percentages of volume pumped and cost of energy in the peak and off-peak times do not vary significantly for the different scenarios. Slightly less volume is pumped in the peak time (there are 70 peak hours in the week and 98 off-peak hours), with peak volumes ranging from 43-49% of total volume and off-peak volumes ranging from 51-57%. The cost of pumping in the peak time is greater than that in off-peak, 57-61% of total cost occurs in peak times compared to 39-43% in off-peak, because of the higher electricity price.

Table 6.6: Comparison of simulation results for Scenarios B_{winter}-V_{winter} to that of Scenario A_{winter} (Baseline Case)

Scenario	What has been changed? Trigger Levels	Pumps	Storage Tank	Total Cost Diff. (%)	Pump Switch Diff. (%)	Cost to Harvest 3 ML ($)	Diff. in Cost to Harvest 3 ML (%)
A_{winter}			[2]36 kL	0	0	265	0
B_{winter}	Wide		36 kL	-4	-10	264	-1
C_{winter}		New	36 kL	-35	-31	135	-49
[1]D_{winter}	Wide	New	36 kL	-37	-41	132	-50
E_{winter}			72 kL	-1	-1	262	0
F_{winter}	Wide		72 kL	-3	-11	266	-1
G_{winter}		New	72 kL	-35	-35	135	-49
H_{winter}	Wide	New	72 kL	-36	-43	131	-50
J_{winter}			180 kL	-2	-8	261	-2
K_{winter}	Wide		180 kL	-2	-15	262	-1
L_{winter}		New	180 kL	-34	-39	135	-49
M_{winter}	Wide	New	180 kL	-34	-50	126	-53
N_{winter}			360 kL	-2	-8	263	-1
P_{winter}	Wide		360 kL	-1	-17	258	-3
Q_{winter}		New	360 kL	-35	-40	136	-49
R_{winter}	Wide	New	360 kL	-30	-58	127	-52
S_{winter}		[3]1, 2	36 kL	-25	+38	200	-25
T_{winter}	Wide	1, 2	36 kL	-27	+46	201	-24
U_{winter}		1, 2	72 kL	-25	+97	200	-25
V_{winter}	Wide	1, 2	72 kL	-27	+341	196	-26

[1]Boxed items correspond to scenarios with the 'best values' in Table 6.5.
[2]Current Storage Tank size is 36 kL.
[3]In Scenarios S_{winter} – V_{winter}, new pump models were considered for Pumps 1 and 2 only, with the current model used for Pump 3.

Comparison of Simulation Results for Different Streamflow Series

Table 6.7 compares the results averaged over all scenarios for each streamflow series. A higher average flow in a streamflow series does not necessarily mean that the volume of water injected will be greater; the variability of the flow and the number of days with a flow rate less than 7 L/s (the maximum confined aquifer injection rate) also has an impact. Series 1 and Series 6 both have flows consistently above 7 L/s; a large increase (157%) in the average flow rate from Series 1 to Series 6 results in a small increase (8%) in the volume harvested. Series 4 and Series 6 have similar average flow rates, however, Series 4 has two days with flow rates of less than 7 L/s, which results in a 19% reduction in the volume of stormwater harvested. Series 4 and Series 5 both have two days with flows below 7 L/s, the average flow rate for Series 4 is almost double (93% increase) that of Series 5, however, the volume of stormwater harvested for Series 4 is only slightly less (6%) than that for Series 5. This is caused by the variability of flow in Series 4, which has a standard deviation 153% times than that of Series 5. As expected, the total cost of pumping for each series increases with the volume of water harvested and injected.

Table 6.7: Comparison of simulation results for each streamflow series (averaged across all scenarios A_{winter}-V_{winter})

Streamflow Series	Average Streamflow (L/s)	Standard Deviation of Flows	Number of Days with Flow < 7 L/s	Cost Rate (c/kL)	Total Cost ($/wk)	Volume Injected (ML/wk)
1	9.90	0.81	0	6.287	208	3.30
2	10.2	8.09	4	6.406	117	2.77
3	2.79	1.44	7	6.631	72	1.09
4	26.4	23.5	2	6.489	187	2.88
5	13.7	9.30	2	6.308	193	3.05
6	25.4	2.88	0	6.087	217	3.56

6.4.3 Simulation Sensitivity Analysis Results – Summer System (Confined Aquifer Extraction and Irrigation)

Results from the simulation sensitivity analysis of the winter system suggested that increasing the tank size would not provide a significant pumping cost reduction. Moreover, space restrictions of the site mean that it is unlikely that increasing the tank size by five or ten times would be considered worthwhile and it is also likely to be very expensive. Therefore, in the simulation sensitivity analysis of the summer system, only the current and doubled tank sizes have been considered. This resulted in eight scenarios with different combinations of current or wide trigger levels in the Storage Tank, current or new Pump 3, and a Storage Tank size of 36 kL or 72 kL (Table 6.8).

Table 6.8: Simulation sensitivity analysis scenarios for the summer system

Scenario	Trigger Levels		Pumps		Storage Tank	
	Current	Wide	Current	New	36 kL	72 kL
	ST: 70-90%	ST: 20-90%	Q_3 = 7 L/s	[3]Q_3 = 7 L/s		
A_{summer}	X		X		X	
[1]B_{summer}		X	X		X	
C_{summer}	X			X	X	
[1]D_{summer}		X		X	X	
E_{summer}	X		X			X
[2]F_{summer}		X	X			X
G_{summer}	X			X		X
H_{summer}		X		X		X

[1]For scenarios B_{summer} and D_{summer}, a lower trigger level of 40% was used because with a lower trigger level of 20%, the tank will drain when the demands are greater than the bore pump flow.
[2]Boxed items correspond to scenarios with the 'best values' in Table 6.9.
[3]Pump operating at a higher efficiency point.

There was minimal difference in the results for most variables except for the number of switches for the Bore Pump (Table 6.9). As the irrigation demands remain the same, so does the operation of Pump 3 (although there is a slight difference in cost between the current and new Pump 3) and the volume of water that needs to extracted by the Bore Pump. When the Storage Tank size increased or the trigger levels were widened, the number of switches required by the Bore Pump was reduced. As all the irrigation occurred overnight, the times when the Storage Tank required filling are in blocks and so the operation of the Bore Pump was directly related to the operating capacity of the tank.

Table 6.9: Simulation sensitivity analysis results for the summer system

Scenario	What has been changed?			Cost (c/kL)			Cost ($/wk)	Volume Extracted (ML/wk)	Pump Switches (/day) Bore Pump, Pump 3
	Trigger Levels	Pumps	Storage Tank	Bore Pump	Pump 3	Total			
A_{summer}			[2]36 kL	3.516	3.966	4.682	90.31	1.93	16,1
B_{summer}	Wide		36 kL	3.509	3.966	4.688	89.45	1.91	7,1
C_{summer}		New	36 kL	3.516	3.892	4.663	89.70	1.92	16,1
D_{summer}	Wide	New	36 kL	3.509	3.892	4.660	89.40	1.92	7,1
E_{summer}			72 kL	3.509	3.966	4.679	90.00	1.92	8,1
[1]F_{summer}	Wide		72 kL	3.509	3.966	4.695	89.09	1.90	2,1
G_{summer}		New	72 kL	3.509	3.892	4.657	89.58	1.92	8,1
H_{summer}	Wide	New	72 kL	3.509	3.892	4.672	88.67	1.90	2,1

[1]Boxed cells in represent the 'best values' for each variable, scenarios that resulted in these 'best values' are boxed here and in Table 6.8.
[2]Current Storage Tank size is 36 kL.

6.5 Optimization

6.5.1 Revised Optimization Model Formulation

The formulation of the optimization problem was revised on the basis of the sensitivity analysis results. They showed that there was little benefit in increasing the size of the storage tank, therefore optimization of pump operations was considered with only the current tank size either with (A) the current pumps or (B) the newly sized pumps. In the winter system, both the cost and volume objectives were considered. The cost was calculated as the cost of energy used by Pumps 1, 2 and 3 to the confined aquifer divided by the volume pumped by Pump 3 (in units of c/kL) and the volume objective was measured as the volume pumped by Pump 3. In this case, the cost objective was calculated relative to the volume pumped so that it was more easily comparable to the cost of potable water.

For the summer system, only the cost objective was considered, and it was calculated as the total cost of energy used by the Bore Pump and Pump 3. As the system pumps to meet demand, the volume pumped does not change between different solutions and therefore it was not necessary to take it into account in the objective functions. Different potential solutions may have resulted in different storage tank levels at the end of the summer irrigation period, however, it was considered undesirable to have more water in the Storage Tank at the end of summer than at the start, as this water would then be pumped back into the confined aquifer when the winter harvesting season started. As extraction from and injection to the confined aquifer are both energy intensive, solutions that extracted more water than was required in summer were not as good as those that extracted the exact demand amount. Constraints were applied for a maximum number of pump switches of 48 per day (less than the current operation) for all pumps, a maximum pressure of 45 m and minimum velocity of 1.1 m/s (equivalent to flow of 7 L/s) downstream of Pump 3 when injecting and a maximum pressure of 40 m downstream of Pump 3 when irrigating.

For the winter system, there were six trigger level decision variables to be optimized (Table 6.10) and four trigger level values that were set and not optimized. Possible choices for the trigger level values ranged from 10% to 100% of the storage volumes, in 10% increments. For the summer system, there were two trigger level decision variables and 22 irrigation scheduling decision variables (two each for 11 open space reserves). In fact, given that the demand rate and duration for each open space reserve (Table 6.2) were set, and the number of days per week, only the start day and time of the irrigation need to be found by the optimization process. Note that the number of days between each irrigation event was fixed for all open space reserves in the system and set equal to one (i.e. irrigation occurs every second day). All open space reserves excluding Unley Oval were irrigated twice a week, and had choices of initial irrigation days of Monday or Tuesday. Unley Oval was irrigated three times a week and could only start irrigation on Sunday. Possible start times for all open space reserves ranged from 8pm to 11:30pm in 30 minute increments. For the summer period, the Bore Pump was controlled by the two trigger level decision variables, which were levels in the Storage Tank (ranging from 10% to 100% in 10% increments).

Table 6.10: Optimization decision variables and set trigger levels for the winter system

Rule	Condition(s)		Effect	Restriction
	Set	Optimized		
1	Harvest Pond level > 0.2	AND Bioretetion level < a[1]	Pump 1 On	b > a
2	Harvest Pond level ≤ 0.2	OR Bioretention level ≥ b	Pump 1 Off	
3	Bioretetion level > 0.13	AND Storage Tank level < c	Pump 2 On	d > c
4	Bioretention level ≤ 0.13	OR Storage Tank level ≥ d	Pump 2 Off	
5	-	Storage Tank level < e	Pump 3 Off	f > e
6	-	Storage Tank level ≥ f	Pump 3 On	

[1]Decision variables are a, b, c, d, e and f.

6.5.2 Optimization Results – Winter System (Stormwater Harvesting and Confined Aquifer Injection)

Using the looped streamflow method (with the streamflow series in Figure 6.6), Pareto fronts were developed for both system configurations (current and new pumps) as shown in Figure 6.7. Note that in all of the Pareto fronts presented in this section, the 'best' solution would be the one closest to the top left corner of the plot (maximizing volume harvested on the vertical axis and minimizing the cost rate on the horizontal axis). Moving from the front for System A to that for System B provides a large improvement in the Pareto solutions, which indicates the effect of replacing the pumps. The new pumps were also able to harvest more water, with the front for System B extending to over 3.5 ML/week, while the fronts for System A did not quite reach 3.0 ML/week. In order to supply all of the summer irrigation demands from harvested stormwater (therefore not using potable supply), a harvest volume of 2.0 ML/week is required on average.

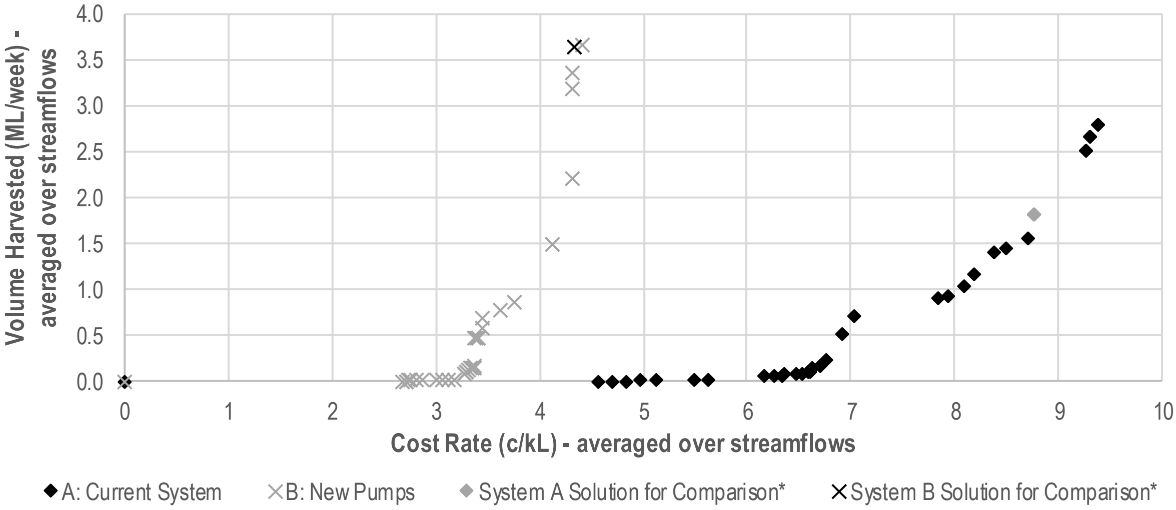

Figure 6.7: Pareto fronts for both system configurations using the looped streamflow method
***Solutions compared to current operation in Table 6.11**

The Pareto fronts produced from the individual streamflow method showed small differences between the streamflow series for System A (Figure 6.8) and almost no difference for System B (Figure 6.9). Streamflow Series 3 showed the largest difference in the Pareto optimal solutions compared with the other series. This series had flows consistently below 7 L/s (the maximum confined aquifer injection rate), and therefore the system could not harvest as much when this series was used. For all of the other streamflow series, the average inflow was above 7 L/s, and while the variability of flow and number of days with flow below 7 L/s made a difference in the simulation sensitivity analysis, little impact is shown in the optimization results. The individual streamflow method may show more variability in results for systems that have a capacity much higher than the average streamflow.

For each system configuration using the looped streamflow method, a solution from the Pareto front that represented a good trade-off between the objectives was chosen for comparison to the current operation (Table 6.11, note that the selected solutions are highlighted in Figure 6.7). System A shows a small improvement, while the new pumps in System B shows a significant cost rate reduction of 50%.

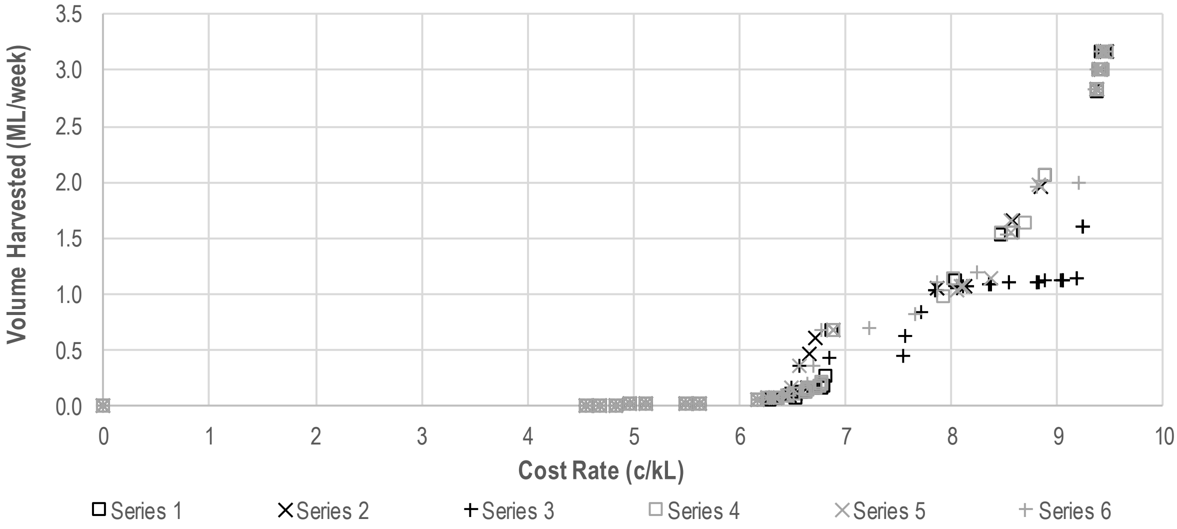

Figure 6.8: Pareto fronts for System A using the individual streamflow method

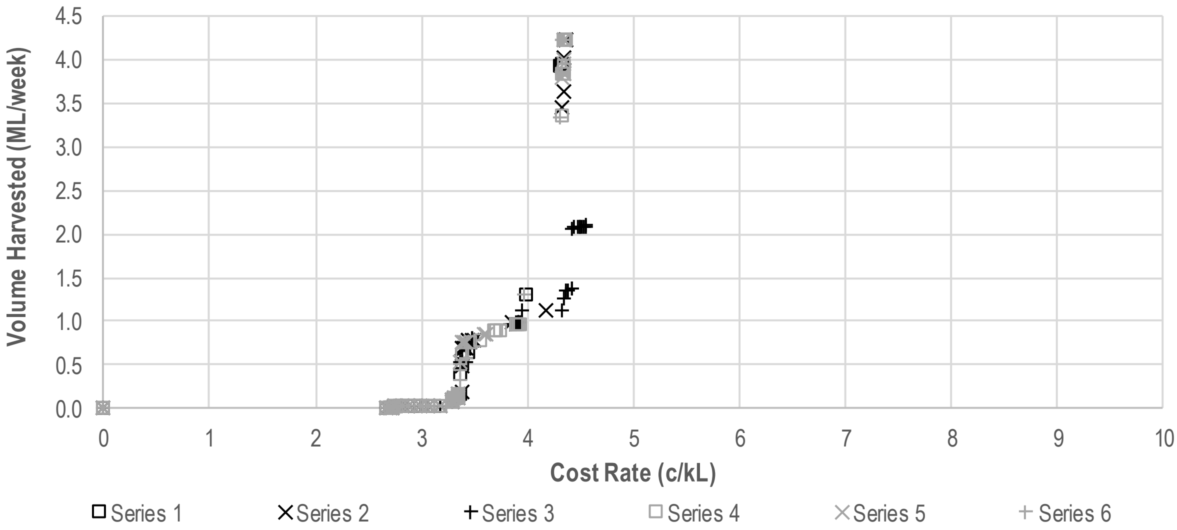

Figure 6.9: Pareto fronts for System B using the individual streamflow method

Table 6.11: Comparison of cost and volume harvested of Pareto optimal solutions to current operation for the winter system

Variable	Current Operation[1]	System A Optimal Solution		System B Optimal Solution	
		Actual	Difference	Actual	Difference
Cost Rate (c/kL)	8.85	8.71	-1%	4.34	-51%
Volume Harvested (ML/week)	2.50	1.84	-26%	3.63	+47%

[1]Data for the current operation is taken from the simulation sensitivity analysis Scenario A

6.5.3 Optimization Results – Summer System (Confined Aquifer Extraction and Irrigation)

Cost reductions for the summer system could be achieved both with the current pumps and by replacing Pump 3 (Table 6.12). The optimal solutions for both systems use trigger levels of 0.25 m (10%) and 2.25 m (90%) in the Storage Tank to control the bore pump. These are much wider than the current trigger levels, utilizing 80% of the Storage Tank volume rather than 20%. Optimal irrigation schedules for both systems have the two Ridge Park stations and Fraser Reserve (i.e. all demand points on the pressure line) irrigated on the same night. For both the current Pump 3 and the new Pump 3, efficiencies are improved with the higher flow rate of all three of the pressure demand points rather than the flow rate required for only one or two demand points. Irrigation of some open space reserves on the gravity line was then deferred to other nights, in order to distribute the irrigation more evenly, preventing the Storage Tank from draining if the Bore Pump could not keep up with higher demands (Figure 6.10 compared to Figure 6.2).

Table 6.12: Comparison of cost of Pareto optimal solutions to current operation for the summer system

Variable	Current Operation	System A Optimal Solution		System B Optimal Solution	
		Actual	Difference	Actual	Difference
Cost ($/week)	$90.3	$85.3	-6%	$82.4	-9%
Cost Rate (c/kL)[1]	4.74	4.47		4.32	

[1]The cost rate is based on the volume irrigated, which is the same for all solutions

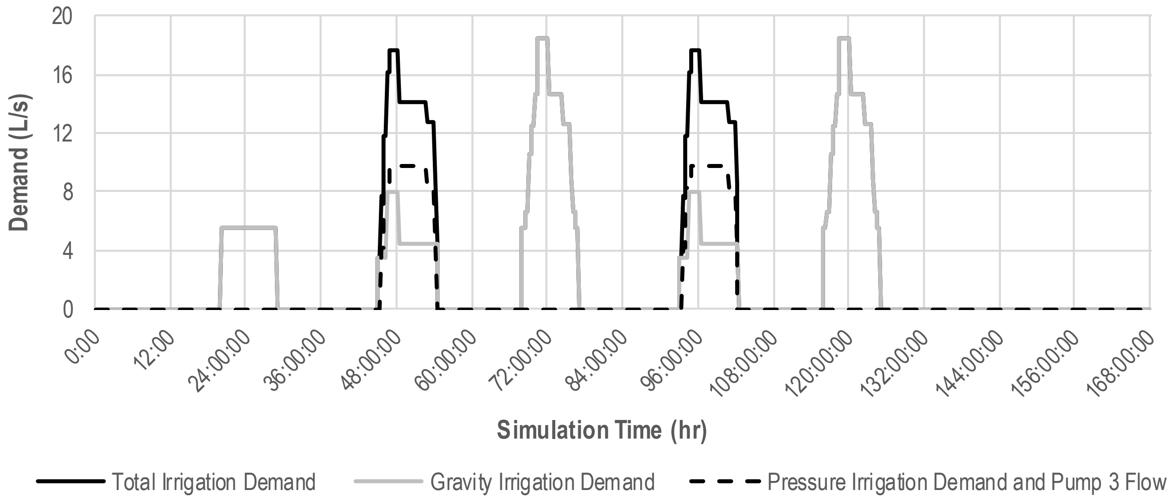

Figure 6.10: Irrigation schedules for the optimized operation for System B

While installing new pumps would be a significant investment, the amount of operational savings may make it worthwhile to the system manager. The difference in cost rate from the optimized operation with the current pump to the optimized operation with new pumps is 4.43 c/kL in winter and 0.15 c/kL in summer. If the full irrigation demand of 52 ML is harvested in winter and supplied in summer, this amounts to $2381 in savings per year. The cost of the newly sized pumps was estimated to be just under $9000. Using a discount rate of 6% over a 20 year period, the net present value of replacing the pumps comes to over $18 000. This indicates that replacing the pumps would be financially beneficial for the Council.

6.6 Conclusions

The operation and system configuration of a harvested stormwater and managed aquifer recharge system has been thoroughly analyzed both through simulation sensitivity analysis and optimization. Simulation of the system was split between the winter operation of harvesting and confined aquifer injection and summer operation of confined aquifer extraction and irrigation. The simulation sensitivity analysis considered replacing the pumps with smaller, more efficient models, increasing the size of the Storage Tank and using wider trigger levels. Replacement of the pumps with smaller models was also considered in the optimization of the system. Different streamflow (input) series have been investigated using two methods in the optimization; firstly by performing separate optimizations (and therefore developing separate Pareto fronts) for each series, and secondly by looping the streamflow series within the optimization to find robust solutions.

Simulation sensitivity analysis of the system found that increasing the size of the Storage Tank would not provide significant benefits, however, installing smaller pumps with better efficiencies could reduce costs by 30-37%. Optimization with these new smaller pumps could provide further savings of up to

50% of current operational costs, and this would provide a net financial benefit. The new pumps were also able to harvest a greater volume over the one week simulation period than the current pumps. Installing new pumps had more of an impact in the winter system, which utilized three new pumps, than in the summer system which only utilized one new pump. Without replacing the pumps, using wider trigger levels, particularly in the Storage Tank during summer, as well as irrigating the three demand points on the pressure irrigation line at the same time could provide reductions in operational costs of 6%. These results suggest that the design of the system may limit the possible savings able to be achieved by operational changes. The case study system analysis in this research was not particularly sensitive to changes in streamflow; when there was adequate water available, regardless of the magnitude and variability of streamflow, the optimal operations were much the same.

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Chapter 7 Conclusions and Future Work

7.1 Thesis Summary

Water supply and distribution systems are a critical part of our society. As climate change and a growing population put pressure on existing supplies, alternative sources such as harvested stormwater are becoming more commonly used. Energy use of pumps is a significant concern for water supply systems, both in terms of cost of electricity and emissions of GHGs. Pump operations have been extensively analysed and optimized for traditional water distribution systems, however, complex pump operating rules have not previously been considered. Optimization techniques have not previously been applied to the minimization of cost of pump operations in alternative water source systems. These systems are generally more complex to simulate and optimize, as there are additional processes, such as streamflow, and additional components, such as treatment wetlands that may need to be considered. This thesis addressed these gaps through the following six objectives developed in **Chapter 1**:

Objective 1. To develop a framework to optimize alternative water system pump operations for multiple objectives including minimizing cost and maximizing volume harvested.

Objective 2. To apply the use of new rule-based controls in a modified EPANET2 programmer's toolkit to optimize complex pump operational strategies using a combination of trigger levels and scheduling, and variable trigger levels.

Objective 3. To optimize pumping operations and irrigation scheduling for short time horizons for systems using harvested stormwater with aquifer storage and recovery and multiple pumping stations.

Objective 4. To demonstrate the importance of performing detailed simulation analysis of water systems in order to better understand the system and to inform optimization of the system.

Objective 5. To analyse the sensitivity of optimal pump operations to changes in streamflow (system inflow) and system design in a stormwater harvesting system.

Objective 6. To minimize GHG emissions from pump operations where operational characteristics are considered as decision variables and characterize trade-offs between optimal cost and optimal GHG solutions for these problems.

Optimization of five different types of pump operating controls has been performed on two potable water distribution system case studies using rule-based controls in EPANET. Minimization of energy costs and GHG emissions were considered separately using a single-objective genetic algorithm. VSP scheduling was found to perform better than the other types of pump operating controls, and significant cost savings were achieved for the real-life South Australian case study. A framework has been developed to demonstrate how these types of optimization tools could be applied to water systems that use alternative sources. The framework incorporates design and operational options, water and electrical energy infrastructure, simulation models, government policy, and objectives and constraints within an optimization algorithm process. This framework was then applied to pump operations in a integrated supply system with multiple alternative water sources and a harvested stormwater system, in order to minimize pump energy costs and maximize the volume of water harvested. An extensive simulation sensitivity analysis was performed on a case study stormwater system, demonstrating the importance of pump selection. Optimization of the system found optimal pump operating strategies for both individual streamflow (input) series and solutions that were robust to multiple streamflow series. As well as replacing the pumps in the system, altering the tank trigger levels and irrigation schedule provided a reduction in pump operating costs.

7.2 Research Contributions

The overall contribution of this research is the application of pump operations optimization techniques that have been successfully developed on traditional potable WDSs to systems that utilize alternative water sources such as harvested stormwater. From the publications presented in **Chapters 4 to 6** of this thesis, the following key contributions have been made to address the knowledge gaps identified in Section 2.4:

The first contribution is the development of a framework for the optimization of systems using alternative water sources (**Objective 1**). This framework describes a methodology for optimization of both design and operations of water systems that use alternative water sources, incorporating options (decision variables), infrastructure, simulation models, and analysis of objectives and constraints. It also identifies interactions between different system components, in particular the integrated nature of water and energy systems, as well as the influence of government policies. Other frameworks and methodologies presented previously have not covered the same extent of both supply and distribution sides of WDSs, or the range of alternative water sources considered in this framework. The framework is generalized, and while its application to two case studies for optimal pump operations is demonstrated in **Chapter 5**, it could be used for both design and operations of other alternative water source systems.

The second contribution is an improved understanding of the optimization of complex pump operating rules including the combination of trigger levels and scheduling (**Objective 2**). Application of the new EPANET Toolkit To Alter Rule-Based Controls (ETTAR) allowed five different pump operating control cases to be investigated for two case study systems in **Chapter 4**. Previous studies have considered trigger levels and scheduling separately, or where combined trigger levels and scheduling were used, only one was formulated as a decision variable, with the other being set before optimization.

Another contribution from **Chapter 4** is the minimization of GHG emissions for pump operations (**Objective 6**). GHGs have been extensively investigated in WDSs, however, this has mainly been in the optimization of the design of systems. These studies do consider pump operations in order to determine life-cycle GHG emissions, however, the operating rules are not considered as decision variables. The work in **Chapter 4** minimizes GHG emissions for existing systems, where pump operating rules are considered as decision variables, rather than the design of the system.

The fourth contribution is the application of optimization techniques developed on traditional WDSs to the operation of a harvested stormwater system (**Objective 3**). Optimization of systems using alternative water sources has not been as extensive as for traditional WDSs, and minimization of pumping costs for systems harvesting stormwater for re-use has not been previously considered. **Chapter 6** extends the work done on potable WDSs to a harvested stormwater system, which is more complex to simulate and therefore to optimize. Irrigation scheduling was optimized along with the pump operating rules; in traditional WDSs, consumer demands cannot be controlled or perfectly predicted and as such represent a constraint or uncertain variable for the system. In systems that use alternative sources for non-potable uses such as irrigation of public spaces, the demands may be controlled by the system managers and therefore considered as decision variables.

The final contribution of this thesis is the demonstration of the importance of extensive pre-optimization simulation and analysis of water systems (**Objective 4**). Before optimization was performed on the case study system in **Chapter 6**, extensive simulation sensitivity analysis was used to refine the optimization problem. Sensitivity of the system to changes in the pump selection, tank size, trigger levels and streamflow was rigorously tested (**Objective 5**). This helped to fully understand the system and to refine the search space of the optimization.

7.3 Recommendations for Future Research

Alternative water source systems are more complex to simulate than traditional WDSs and have different modelling requirements. The harvested stormwater case study investigated in this thesis was simulated in EPANET hydraulic simulation software, however, this may need to be connected to hydrological or hydrogeological models for other systems. For the case study presented in **Chapter 6**, streamflow data was available and this could easily be implemented as an input to the hydraulic model. Generally, streamflow data is much more limited than rainfall data, and therefore other systems may only have rainfall data available. In this case, a hydrological rainfall-runoff model would need to be used to provide input to the hydraulic model. Hydrologic models could also be utilized in order to consider the impacts of climate change on the stormwater runoff volumes and harvesting capacity of stormwater catchments.

Assumptions made about the groundwater aquifer in the case study also meant that it could be represented purely through the hydraulic model, however, in systems with more complex ground and surface water interactions, a hydrogeological model may be required. In order to make the methodology used in the research more generally applicable to other alternative water source systems, hydrological and hydrogeological simulation should be incorporated.

Water quality is another important consideration, for both traditional potable supply and alternative water sources that could be included in the future. This may be done through hydraulic simulation; many programs have at least the ability to calculate water age, if not chemical concentrations as well. Additional code added on to hydraulic simulation or other programs already available for water quality modelling could also be required to accurately account for water quality.

As the focus for this research was on the pumping operation of existing systems in the current climate conditions, there was limited investigation of different streamflow or demand scenarios. Both of these factors are uncertain now and into the future, particularly when climate change is considered. The methodology used for the harvested stormwater case study allowed multiple streamflow inputs to be considered, however, only a small number of recorded data series were used. To make the optimal solutions more robust to current and future variation in streamflow and demand, multiple replicates based on statistics of recorded data and projections should be incorporated. This could be achieved by connecting the methodology in this research with algorithms such as Monte Carlo simulation.

Electricity tariffs are also uncertain into the future; while specific case studies have given electricity tariff structures and prices for the short-term, energy infrastructure and markets will change in the future resulting in different electricity tariffs. The case studies in this research all had relatively simple peak and off-peak electricity tariffs, and one also considered peak demand charge. More complex tariffs such as those with shoulder periods or different weekend tariffs would increase the complexity of the optimisation and should be considered in the future.

The framework presented in **Chapter 5** discusses many different types of alternative water sources, however, only harvested stormwater was investigated further in this thesis. A natural extension of this work would be to apply the framework and methodology to other types of alternative water source systems, such as recycled wastewater, groundwater and imported water. These different sources will each have unique components that need to be simulated, which would not be incorporated in the current methodology developed for the harvested stormwater system. Applying the framework to systems with more complex pumping arrangements would also help to further develop the methodology.

Further development of the methodology on different types of alternative water source systems would make it more generalized and allow easier application to all types of alternative water source systems in the future. An explicit mathematical model of the framework could be developed to allow other researchers to apply it with more consistency and ease.The framework presented in Chapter 5 incorporates optimization in its structure, however, it does not specify a particular algorithm. This study utilized only one type of optimization technique – Genetic Algorithms. Different optimization methods all have different advantages and disadvantages, and the most suitable algorithm will depend on the specific problem. In the future, different optimization tools could be utilized within the framework to determine which performs best for different alternative water source problems.

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Appendix A: Final Published Version of Publication 1 (Chapter 4)

Publication 1 presented in Chapter 4.

Comparison of Pumping Regimes for Water Distribution Systems to Minimize Cost and Greenhouse Gases

Blinco, L.J., Simpson, A.R., Lambert, M.F., and Marchi, A.

School of Civil, Environmental and Mining Engineering

The University of Adelaide, Adelaide, SA 5005 Australia

Journal of Water Resources Planning and Management, 142(6).

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Comparison of Pumping Regimes for Water Distribution Systems to Minimize Cost and Greenhouse Gases

Lisa J. Blinco[1]; Angus R. Simpson, M.ASCE[2]; Martin F. Lambert, M.ASCE[3]; Angela Marchi[4]

Abstract: A single-objective optimization model has been developed for water distribution system (WDS) pumping operations, considering five different types of pump operating regimes. These regimes use tank trigger levels, scheduling, and a combination of both to control pumps. A new toolkit development to alter rule-based controls in hydraulic simulation software has allowed more complex pump operating regimes than have previously been considered to be optimized. The performance of each of the regimes is compared with respect to two different objectives: cost and greenhouse gas (GHG) emissions, which were optimized separately to allow the comparison of regimes to be made more clearly. Two case study networks, including one that represents a segment of the South Australian WDS, illustrate the effectiveness of the model. Time-based scheduling operating strategies were found to perform better than the other types of pump operating regimes. Significant cost savings were achieved for the South Australian case study network compared with its current operation. **DOI: 10.1061/(ASCE)WR.1943-5452.0000633.** © *2016 American Society of Civil Engineers.*

Author keywords: Optimization; Pump operation; Genetic algorithm; Greenhouse gas emissions; Water distribution systems.

Introduction

Energy costs can account for up to 65% of a water utility's operating budget (Boulos et al. 2001), and as such optimizing the cost of energy used for pumping will have significant benefits. Previous investigations of optimal pump operating strategies have generally been restricted to either lower and upper tank trigger levels or scheduling. Consideration of more complex pump operating regimes, for example, using trigger levels that vary throughout the day or combining trigger levels and scheduling, has been restricted in part by simulation model capabilities. A modification of the existing EPANET2 toolkit (Rossman 2000) has been developed by Marchi et al. (2015) in order to modify rule-base controls. This new toolkit is called "EPANET2-ETTAR" (EPANET2 Toolkit to Alter Rules) and allows more complex pump operating regimes to be optimized. Human-induced climate change presents a serious global risk and action to mitigate the impact by reducing greenhouse gas (GHG) emissions is important. Production of electrical energy for water distribution system (WDS) pumping operations is the biggest contributor to GHG emissions from the water industry (Stokes and Horvath 2006; Wu et al. 2013).

This paper describes the development of a single-objective genetic algorithm (GA) optimization model for WDS pump operations integrating *EPANET2* (including EPANET2-ETTAR) and a Microsoft Excel interface. The performance of five different types of pump operating regimes, including trigger levels that vary throughout the day and combined trigger levels and scheduling, is compared with respect to either the minimization of cost or the minimization of GHG emissions. The model is applied to two different case studies, a hypothetical one-pipe network and a real-life network from South Australia. In the second case study, two different pump sizes are considered and the results compared.

Literature Review

Efficient operation of WDSs can be achieved in several ways. The first step is to optimize the design of pumps and infrastructure, then, for existing or designed systems, pump operating rules can be optimized. Other strategies include recovering energy that would otherwise be dissipated using mini-hydro systems (Carravetta et al. 2013b; Fecarotta et al. 2015), reducing leakage to reduce pump and water treatment energy requirements (Giustolisi et al. 2013) and pump maintenance or replacements. There are many different objectives that can be considered to achieve efficient WDS operation, with the most common being to minimize the cost of electrical energy use. GHG emissions, based on energy use, or simply energy use itself can be used as environmental impact objectives (Simpson 2009). Water quality can be addressed by minimizing water age, which can be obtained from *EPANET2* (Stokes et al. 2012a); pump maintenance cost, represented by pump switches, could be formulated as an objective (López-Ibáñez et al. 2005) or as a constraint (Lansey and Awumah 1994); system effectiveness (Carravetta et al. 2013a), resilience (Prasad and Park 2003), and leak reduction (Giustolisi et al. 2015) can also be used as objectives to improve the performance of WDSs.

The research presented in this paper focuses on the optimization of pump operating rules and the comparison of different types of

[1]Ph.D. Candidate, School of Civil, Environmental and Mining Engineering, Univ. of Adelaide, Adelaide, SA 5005, Australia; Cooperative Research Centre for Water Sensitive Cities, Melbourne, VIC 3000, Australia (corresponding author). E-mail: lisa.blinco@adelaide.edu.au

[2]Professor, School of Civil, Environmental and Mining Engineering, Univ. of Adelaide, Adelaide, SA 5005, Australia; Cooperative Research Centre for Water Sensitive Cities, Melbourne, VIC 3000, Australia. E-mail: angus.simpson@adelaide.edu.au

[3]Professor, School of Civil, Environmental and Mining Engineering, Univ. of Adelaide, Adelaide, SA 5005, Australia; Cooperative Research Centre for Water Sensitive Cities, Melbourne, VIC 3000, Australia. E-mail: martin.lambert@adelaide.edu.au

[4]Postdoctoral Researcher, School of Civil, Environmental and Mining Engineering, Univ. of Adelaide, Adelaide, SA 5005, Australia; Cooperative Research Centre for Water Sensitive Cities, Melbourne, VIC 3000, Australia. E-mail: angela.marchi@adelaide.edu.au

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pump operating structures. The case studies investigated are existing systems, and therefore no design optimization is considered. Objectives of pumping electricity cost and GHG emissions are considered separately and the characteristics of the optimal operating strategies for the objectives are compared. Multiobjective optimization of cost and GHG emissions for WDSs has been extensively covered in Wu et al. (2010a, d, 2011, 2012a, b, 2013) and Stokes et al. (2012b, c, 2014). This research is different in that it considers the effect of the different pump operating regimes on each objective individually.

WDSs are often required to perform under different conditions, including different demands (e.g., seasonal and daily variations), emergencies (such as fires), and failure scenarios (such as power outages or pipe breaks), all of which have some uncertainty associated with them. Goryashko and Nemisrovski (2014) use stochastic methods to find optimal operating strategies that are robust to different demand scenarios, while Basupi and Kapelan (2015) combine Monte Carlo analysis with GA optimization for the WDS design problem. Analysis of emergency conditions and system failure in optimization has been much more widely applied to the design problem (e.g., Morley et al. 2012) while, for pumping operations, the use of a constraint on the minimum tank level or an emergency reserve storage is usually used to guarantee a reliable service.

Optimization of pump operations is highly complex due to a large number of possible pump operating strategies, variable electricity price, and fluctuating consumer demands. Operational policies are also subject to several constraints, including acceptable levels of water in storage tanks, maximum pumped volumes, long-term tank level balancing, nodal pressure limits, and maximum pipe velocities. Previous studies have usually been restricted to using either trigger levels (Paschke et al. 2001; Stokes et al. 2012b) or scheduling (Mackle et al. 1995; Goryashko and Nemisrovski 2014) and have not considered more complex operations such as trigger levels that vary throughout the day or combinations of trigger levels and scheduling. Lower and upper trigger levels represent the tank levels at which the pump(s) will turn on or off, respectively (when pumping to a downstream tank). Pump scheduling involves a set of temporal rules indicating when pumps should be switched on or off during the day. Scheduling requires an accurate estimation or a forecast of the expected daily water demand. Kazantzis et al. (2002) combined the use of trigger levels and scheduling, however, the trigger levels were fixed, and only the scheduling variables optimized. In *EPANET2* (Rossman 2000), only simple controls (used for trigger levels) and pump patterns (used for scheduling) can be altered through the programmer's toolkit (which can be used to trial different potential solutions within, say, a genetic algorithm optimization framework), and rule-based controls that are required for more complex operating regimes cannot be changed via the current toolkit. EPANET2-ETTAR gives access to these rule-based controls, therefore allowing more complex pump operating regimes to be considered in the pumping optimization process.

When a peak and off-peak electricity tariff structure applies, operational costs will be minimized by reducing the amount of pumping in the peak electricity period and deferring this pumping to the off-peak period. Operational costs will also be reduced by reducing the static head and by increasing the efficiency of the operating point. Maximizing the amount of off-peak electricity pumping can generally be achieved when the tank water level is at its maximum at the beginning of the peak period and at its lowest allowable level at the end of the peak period (Mackle et al. 1995; Kazantzis et al. 2002). A future approach, primarily concerned with GHG emissions, may be to pump steadily throughout the day with a variable speed pump (VSP), or in response to demands rather than electricity prices, with reduced energy through the use of slower velocities leading to a smaller friction head loss (Simpson 2009).

To properly account for the GHG emissions of WDSs, the sources of electricity should be identified because each will have different GHG emissions per unit of energy produced (Dandy et al. 2006). An emission factor is used to convert energy use to GHG emissions, considering all types of GHGs and their global warming potential as an equivalent mass of CO_2 (CO_2-eq). Previous studies have used an average GHG emission factor value for the region, including Dandy et al. (2006) and Wu et al. (2010a, d). Stokes et al. (2012b) took into account time-varying emission factors in their optimization of water distribution system design and operation. This identified high emission intensity electricity use and helped to reduce operational GHG emissions. The objectives of cost and GHG emissions may be aligned if no variation in electricity tariffs or emission factors is considered. When variations in these factors are taken into account, times with lower electricity prices will not necessarily coincide with times of lower emission factors, so optimal solutions for the two objectives will be different.

GAs represent an efficient method for the optimization of nonlinear problems, particularly when applied to complex WDSs. These algorithms are a population-based optimization technique that use coded representations of solutions (Goldberg 1989). After generating a random initial population, the GA determines the fitness of each potential solution by simulating them and evaluating an objective function. In many optimization problems, the objective function is based on cost, but it can also be formulated for other objectives. All solutions then go through GA operators based on evolutionary principles—typically selection, crossover, and mutation–to produce the next generation of solutions (Goldberg 1994). This process is repeated to converge on optimal or near-optimal solutions. When applied to the optimization of WDSs, GAs have been found to perform significantly better than other optimization techniques in areas of final solution optimality and iterative efficiency and are still competitive with other optimization methods today (Simpson et al. 1994; Wang et al. 2015).

Methodology

Optimization Model Formulation

The aim of this research was to compare the performance of five different pump operating control cases and the characteristics of their optimal solutions. To achieve this aim, a single-objective optimization model was developed, linking a GA with EPANET2-ETTAR and a Microsoft *Excel* Interface. EPANET2-ETTAR was used to simulate the different potential solutions from the GA in order to provide information about their performance relative to the objective function and constraints. The interface allowed the optimization parameters, decision variables, choice tables, and other inputs to be changed and customized for different networks. A single-objective GA with tournament selection, a choice of one- or two-point crossover, and bitwise mutation was used. Trigger level cases, with a small number of decision variables, used one-point crossover with a crossover probability of 0.8, a mutation probability of 0.05, 200 generations, and a population size of 200. Scheduling cases, with a large number of decision variables, used two-point crossover with a crossover probability of 0.7, a mutation probability of 0.02, 400 generations, and a population size of 300.

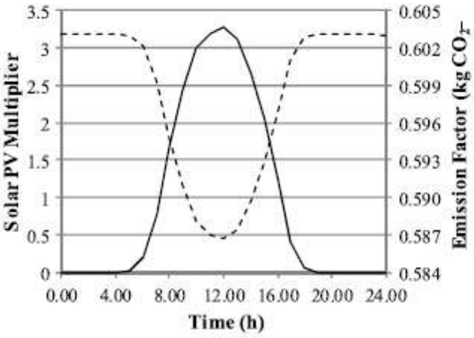

Fig. 1. Daily variation in solar photovoltaic output (solid) and emission factors (dashed)

Wherever possible, full enumeration of the search space was used in preference to the genetic algorithm optimization.

Two different objective functions were considered separately: cost and GHG emissions. The value of each objective function was calculated in terms of units per volume of water pumped to remove any bias between solutions that pumped different volumes of water over the day. For the cost optimization, the objective function was dependent on the energy use, electricity tariff rates, and the volume of water pumped over the whole day as given by Eq. (1)

$$\mathrm{OC} = \frac{\sum_i T_i \times E_i}{V} \tag{1}$$

where OC = operational cost (dollars/m^3); T_i = electricity tariff for each time step i (dollars/kWh); E_i = energy consumption for each time step i (kWh); and V = total volume pumped (m^3) during the time simulation period. EPANET2-ETTAR was utilized to determine energy use for each time period as well as the volume of water pumped. In this research, a two-part electricity tariff has been considered, however, the pattern for the electricity tariff could easily be altered to consider other, perhaps more complex, tariff structures, such as a multipart tariff (more than two periods). In addition, a monthly peak energy demand charge (that is, an additional charge for the maximum kilowatt usage) could also be included if desired. An electricity price pattern can be specified in *EPANET2*, as well as a demand charge variable, which may apply if there is a monthly peak energy demand charge. Electricity costs were based on a representative South Australian tariff; a peak electricity price of 22 c/kWh (c = cents) between 7 a.m. and 11 p.m., and an off-peak electricity price of 9 c/kWh from 11 p.m. to 7 a.m.

The objective function for GHG emissions was based on the distribution of emission factors throughout the day and the energy used in each time period as given by Eq. (2)

$$\mathrm{OGHG} = \frac{\sum_i F_i \times E_i}{V} \tag{2}$$

where OGHG = operational GHG emissions (kg CO_2-eq/m^3); F_i = emissions factor at each time step i (kg CO_2-eq/kWh); and E_i = energy at each time step i (kWh), which ranged from 0 to 23 for hourly time increments. Emission factor data were collated from Dey and Lenzen (2000), Lenzen (2008), and Evans et al. (2010) in order to take into account the varying contributions to GHG emissions from different energy technologies. To calculate the overall emission factor, South Australia's current energy sources, mainly gas, brown coal, and wind (Australian Energy Market Operator 2011), have been used. The emission factors were also adjusted to account for the variation in output from solar photovoltaic systems throughout the day and this output was greatest during the middle of the day (Fig. 1). The contribution of each energy source at every hour was adjusted depending on the solar photovoltaic multipliers to give a daily variation in emission factors, which were lowest in the middle of the day (Fig. 1). Minimization of energy consumption was also available in the model and acted as a surrogate for optimization of cost or GHG emissions where no daily variation in electricity tariffs or emissions factors was present.

A number of constraints could be used in the optimization process, with penalties added to the objective function in the case of constraint violation. In addition to pressure, velocity, and head loss constraints, a minimum tank level may be specified to account for emergency and dead storages. There was also a tank balancing constraint, formulated as the maximum allowable difference between the storage tank's start and end level each day, and this could be used to prevent depletion of the water in the tank at the end of the simulation period. The maximum number of pump switches to occur within a 24-h period may also be specified, which could be used to address issues of pump maintenance costs.

Pump Operating Control Cases

Optimization of five distinct pump operating control cases was considered: (1) Case A, lower and upper trigger levels; (2) Case B, a reduced upper trigger level; (3) Case C, combined trigger levels and scheduling; (4) Case D, variable trigger levels; and (5) Case E, variable speed pump scheduling. The pump operation was optimized over a period of 24 h, with the simulation period beginning at the start of the off-peak tariff period and the water level in the tank being at its lowest allowable level. This serves as a known starting point for an optimal solution and also means that the final water level of the tank is likely to be close to the initial level as less pumping will benefit either of the objective functions. The available decision variables and constraints for each pumping control case are summarized in Table 1.

Control Case A optimized two decision variables—the lower and upper trigger levels in a downstream tank that determined when a pump would be switched on and off, respectively. While trigger levels are effective at keeping the water level in a tank within a certain operating range, there are both advantages and

Table 1. Summary of Decision Variables and Constraints for Each Control Case

Case	Decision variables	Constraints
A	Lower trigger level; upper trigger level	Minimum tank level, tank balancing tolerance, maximum pump switches, maximum and minimum nodal pressures, maximum and minimum pipe velocities, maximum and minimum pipe head loss
B	Lower trigger level; reduced upper trigger level; upper trigger level	
C	Lower trigger level; upper trigger level; scheduled pump start(s); scheduled pump stop(s)	
D	Peak lower trigger level; peak upper trigger level; off-peak lower trigger level; off-peak upper trigger level	
E	Pump speed multiplier(s) (number depends on time interval)	

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disadvantages to different trigger level operating strategies. Increasing either trigger level will increase the average static head of the system and therefore requires the pump to expend more energy to pump the same volume of water to the tank. A lower value of the upper trigger level may increase the amount of pumping required in the peak electricity tariff period because the tank will not be full at the start of this period, and hence may increase costs. The closer the trigger levels are to each other, the more times the pump will switch on and off during the day, which will increase general wear and tear of the pumps. Additionally, having both trigger levels or just the lower trigger level closer to the minimum allowable tank level may jeopardize the system's capability to meet demand requirements. In times of extremely high demand, the rate at which the tank is draining may exceed the maximum pumping capacity, resulting in overall depletion of the tank volume even with the pump switched on. In these circumstances, if the trigger levels are too low, the water level in the tank may fall below the minimum allowable level.

A reduced upper trigger level was considered in Control Case B, which implemented EPANET2-ETTAR for optimization of rule-based controls. This model had three decision variables: a lower trigger level, an upper trigger level, and a reduced upper trigger level. During most of the 24-h simulation period, a reduced upper trigger level was permitted in order to reduce the static head of the system. There was a user-selected switch time before the start of the peak period at which the control would swap to the ultimate upper trigger level in order to fill the tank before the peak period.

Control Case C combined the use of tank trigger levels and pump scheduling. There were two trigger level decision variables—an upper and lower trigger level—which governed most of the pump operation. In addition to this, multiple time-based scheduling decision variables were also included that would specify a time for pump starts and pump stops. These time-based decision variables allow the tank water level criteria at the end of each tariff period [as identified by Mackle et al. (1995) and Kazantzis et al. (2002)] to be met where trigger levels alone cannot achieve this. For example, if the trigger levels in a particular network were such that the tank was draining at the end of the off-peak period, a scheduled pump start was added so that the tank is full at the start of the peak period. If the tank is filling at the end of the peak period, a scheduled pump stop was added to ensure the tank would be at its lowest allowable level at the end of the peak period and therefore avoid excess peak pumping.

Control Case D allowed for different trigger level sets for the peak and off-peak periods and this also utilized the EPANET2-ETTAR toolkit. There were four decision variables—an upper and lower trigger level in the peak period and an upper and lower trigger level in the off-peak period. In order to reduce the pumping cost, the two trigger levels used for the off-peak period will be higher than the two trigger levels used for the peak period because this allows the tank level to be closer to full at the beginning of the peak tariff period and close to the minimum allowable tank level at the beginning of the off-peak period. As suggested by Kazantzis et al. (2002), in order to optimize costs the tank should be at its minimum level at the end of the peak period and at its maximum level at the start of the peak period. The two different sets of trigger levels also allow for the reduction of the static head (and therefore energy use) during the period of higher electricity cost.

VSPs were incorporated into Control Case E, which optimized pump scheduling regimes. The decision variables in this model were the pump speed multipliers at each time interval. If fixed-speed pumps (FSPs) were used, the only possible values for the pump speed multipliers would be 0 or 1. For VSPs, additional choices for the multipliers could range from 0.85–1.0 (as well as 0 for when the pump is off). The minimum pump speed multipliers calculated for the specific case studies take into account the guidelines by Marchi et al. (2012): (1) the minimum relative speed of the pump is larger than 0.7 so that the affinity laws can be used to predict the pump efficiency curve with reasonable accuracy, and (2) the shutoff head of the pump curve at the reduced speed is still higher than the static head of the system in order to deliver a flow larger than zero. In particular, the lower limit (0.85 in this case) depends on the pump shutoff head relative to the maximum system static head. Variable speed drive efficiency is not taken into account and this could affect the energy use of VSP solutions (Walski et al. 2003). When choosing a VSP for a particular system, the overall efficiency, including the variable speed drive efficiency and motor efficiency, should be taken into account. The time interval for the simulation of the pump schedule could be modified to reflect different demand patterns and pumping restrictions or requirements. For example, half-hourly time intervals would result in 48 decision variables, which could increase operational flexibility but also could increase optimization run times and effectiveness compared with hourly time intervals with only 24 decision variables. For systems with multiple pumps, a larger time interval may need to be used because otherwise the number of decision variables may easily become excessive, leading to long optimization run times and a larger search space, making finding the optimal solution more difficult.

Results

Case Study 1: One-Pipe Network

The models were initially used to analyze a one-pipe network introduced by Wu et al. (2010a), who performed a multiobjective optimization for the pump size and pipe diameter of the network, finding eight nondominated solutions in terms of capital and operating costs and GHG emissions. A design solution that represented an acceptable trade-off between costs and GHG emissions was used in this research (Fig. 2 shows the network configuration). The network pumped water from an upstream reservoir to a downstream tank, which supplied an average peak day demand of 80 L/s. A diameter of 20 m was assumed for the downstream circular tank. Potential trigger level values for this network ranged from 1.0 to 5.0 m, with an increment of 0.2 m. The minimum possible trigger level value accounted for dead storage and emergency reserves. VSP multipliers considered were between 0.85 and 1.0 in 0.05 increments (Table 2). The minimum feasible VSP multiplier was determined using the first pump affinity law relationship between pump head (H_P) and speed (N) [Eq. (3)]. Pump speed can be reduced to a point where the shutoff head of the pump is equal to the static head of the system. At full speed [1,475 revolutions per minute (rpm)], the pump shutoff head is 143 m (H_{P1}) and the static head of the system when the tank is full is 100 m (H_{P2}). Applying Eq. (4) gives a minimum pump speed multiplier (N_2) of 0.84; to be

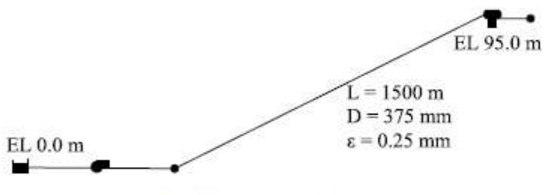

Fig. 2. One-pipe network

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Table 2. Summary of Choices and Constraints Applied to Each Case Study

Decision variable or constraint	One-pipe network	South Australian network
Trigger levels (Cases A–D)	1.0–5.0 m, 0.2-m increment	4.0-7.9 m, 0.1-m increment
First pump start (Case C)	3 to 7 a.m., 5-min increment	3 to 7 a.m., 5-min increment
Second pump start (Case C)	4 to 10 p.m., 5-min increment	—
Pump stop (Case C)	10 to 11:30 p.m., 5-min. increment	6 to 10 p.m., 5-min increment
Pump speed multipliers (Case E)	0.85–1.0, 0.05 increment	0.88–1.0, 0.04 increment
Minimum tank level	None, 0.8, 1.0 m	2.5, 4.0 m
Tank balancing tolerance	None, 0.5 m	None, 0.1, 0.5 m
Maximum pump switches	12, 96	12, 96
Minimum and maximum nodal pressures	—	None, 20 and 120 m
Minimum and maximum pipe velocities	—	None, 0 and 5 m/s
Minimum and maximum pipe head loss	—	None, 0 and 50 m/km

conservative, a minimum value of 0.85 is considered (equivalent to approximately 1,254 rpm)

$$\frac{H_{P_1}}{H_{P_2}} = \left(\frac{N_1}{N_2}\right)^2 \tag{3}$$

$$\text{if } N_1 = 1 \text{ (full speed) then } N_2 = \sqrt{\frac{H_{P_2}}{H_{P_1}}} \tag{4}$$

Control Case A

Cost Minimization. When optimizing pump operating Control Case A, a lower trigger level of 1.0 m and an upper trigger level of 5.0 m was the best solution in terms of cost (Table 3). Because there were only two decision variables, each with 21 possible values (using increments of 0.2 m), the total number of possible solutions was $21^2 = 441$. Complete enumeration of the problem was performed and confirmed this result. The second-best through to the sixth-best solutions as presented in Table 3 show the same characteristic of having the trigger levels far apart, allowing maximum off-peak pumping. Solutions 7, 8, and 10 reduce energy use and therefore cost by reducing the static head of the system. These solutions all had a trigger level range of 1.6 m, with different lower and upper trigger levels. This trigger level range allowed the tank to half-fill twice during the off-peak period while also maintaining a lower water level than the first six solutions (Fig. 3). As can be seen

Table 3. Top Solutions from Pump Operating Control Case A Optimization for the One-Pipe Network

Solution	Cost ($/m³)	Lower trigger level (m)	Upper trigger level (m)	Trigger level range (m)	Energy (kWh/m³)	Peak energy (%)	Off-peak energy (%)	Minimum water level (m)[a]	GHGs (kg CO_2-eq/m³)
Cost: 1st	0.0683	1.0	5.0	4.0	0.3725	72.0	28.0	0.36	0.2222
Cost: 2nd	0.0688	1.0	4.8	3.8	0.3721	73.1	26.9	0.40	0.2220
Cost: 3rd	0.0690	1.2	5.0	3.8	0.3728	73.1	26.9	0.59	0.2224
Cost: 4th	0.0695	1.0	4.6	3.6	0.3718	74.5	25.5	0.48	0.2219
Cost: 5th	0.0696	1.2	4.8	3.6	0.3725	74.4	25.6	0.66	0.2223
Cost: 6th	0.0697	1.4	5.0	3.6	0.3731	74.4	25.6	0.85	0.2227
Cost: 7th	0.0698	1.0	2.6	1.6	0.3702	75.9	24.1	0.77	0.2213
Cost: 8th	0.0699	1.2	2.8	1.6	0.3708	75.8	24.2	0.96	0.2218
Cost: 9th	0.0701	1.0	4.4	3.4	0.3716	75.9	24.1	0.60	0.2218
Cost: 10th	0.0701	1.6	3.2	1.6	0.3721	75.7	24.3	1.32	0.2225
GHG: 1st	0.0721	1.0	1.2	0.2	0.3685	81.2	18.8	0.45	0.2204

[a]Maximum water level for each solution is equal to the upper trigger level.

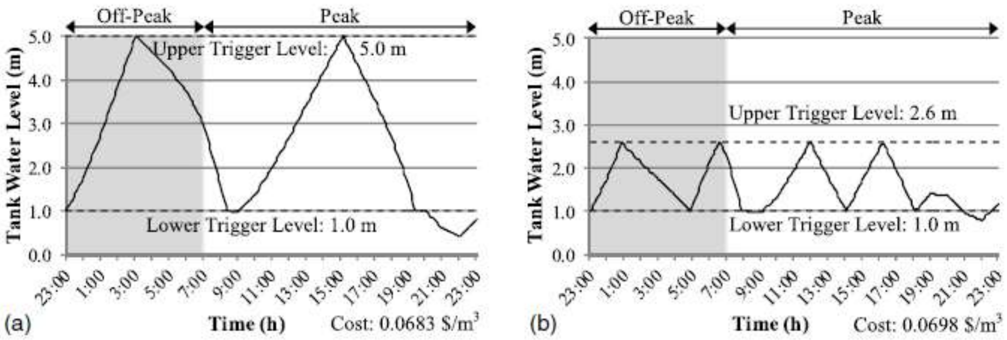

Fig. 3. Daily tank level variation of the one-pipe network: cost optimization solutions: (a) pump operating Control Case A, first solution; (b) Control Case A, seventh solution

in the "Energy" column, the seventh solution had the lowest energy use per volume of water pumped from the cost optimization solutions. It had a greater cost per volume pumped because there is a greater percentage of energy being used in the peak period compared with the first six solutions ("Peak energy" and "Off-peak energy" columns). This indicates that for this network, the effect of the peak and off-peak tariff prices on the cost is greater than the effect of reducing the static head.

The solutions represented in Table 3 and Fig. 3 did not have a minimum tank level constraint enforced, which allowed the water level to fall significantly below the lower trigger level of 1 m due to high demands in the evening ("Minimum water level" column Table 3). If a minimum tank level constraint of 1 m is used, the optimal trigger levels are found to be 1.6 and 3.2 m (the 10th-best solution in Table 3), which has a minimum tank level of 1.32 m, well above the constraint. If the minimum level constraint is relaxed slightly, the optimal trigger levels are found to be 1.2 and 2.8 m (the eighth-best solution in Table 3). This results in a minimum tank level of 0.96 m, which may be acceptable to the decision maker. This shows the impact of the minimum tank level in finding the optimal trigger levels.

GHG Minimization. The optimal solution for GHG emissions was different than the optimal cost solution. The lower and upper trigger levels were as low and as close together as possible, at 1.0 and 1.2 m, respectively (while in the cost optimal solution they were as far apart as possible), reducing the static head. No effect due to the daily variation in GHG emission factors was observed in the optimal GHG solution. Because the trigger levels are very close together, the pump turns on and off quite often (62 pump switches) throughout the day, with the exception of two blocks in the peak period where the pump is on, resulting in higher costs. The seventh cost solution had lower GHG emissions than the other top 10 cost solutions ("GHGs" column of Table 3). Because it reduced energy use and costs by reducing the static head as well as reducing peak pumping, it was an acceptable compromise between the cost and GHG objectives.

Control Case B: Cost Minimization

With the addition of a reduced upper trigger level in Control Case B, the minimum operating cost was lowered to $\$0.0652/m^3$, compared with the $\$0.0683/m^3$ for the Control Case A solution. A switch time of 2 a.m. gave the lowest cost and was able to fill the tank just before the start of the peak period at 7 a.m. [Fig. 4(a)]. Using a reduced upper trigger level did not benefit GHG emissions because there was no need to fill the tank before the start of the peak period and a reduced static head could be achieved using a low value for the upper trigger level.

Control Case C: Cost Minimization

For Control Case C, the combination of trigger levels and scheduling, the cost was reduced slightly compared with the previous control cases at $\$0.0651/m^3$. Due to the high demands at the end of the peak period, shutting the pump down during this time would not be feasible. Therefore, an additional decision variable in the form of a pump startup during the peak time was considered as well as those proposed in the methodology. The time range for this pump startup was 4 to 10 p.m. at an increment of 5 min, which allowed the tank level to stay above 1 m, and a pump shutoff was considered between 10 and 11:30 p.m., also at an increment of 5 min. The optimal cost solution found using this strategy again had wide trigger levels of 1 and 5 m, the pump was started again at

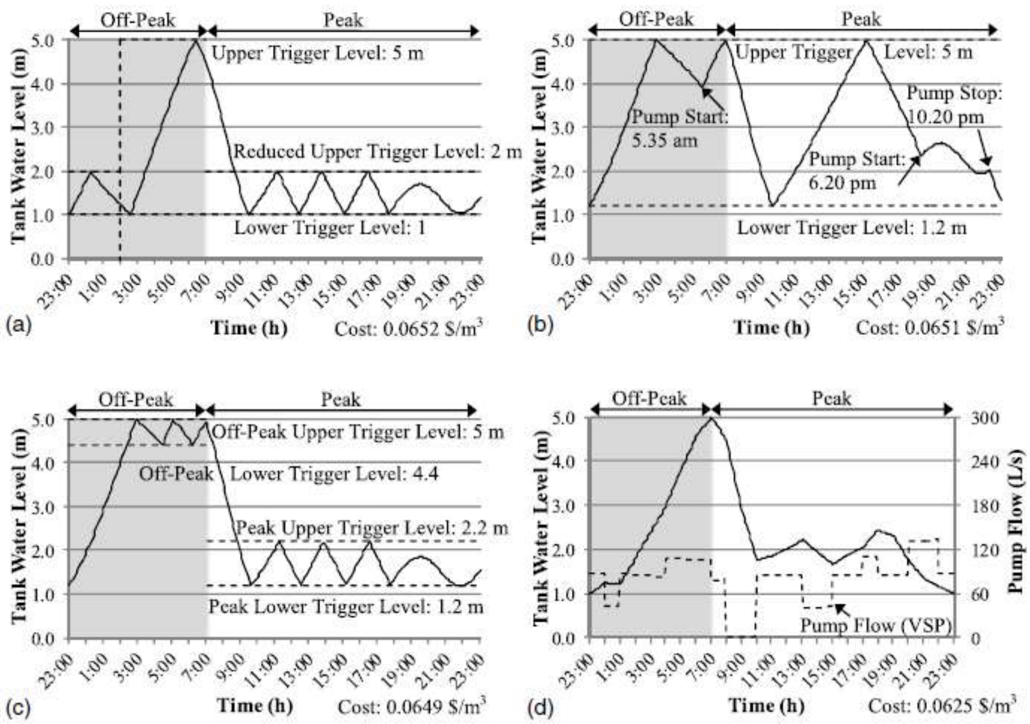

Fig. 4. Daily tank level variation of the one-pipe network: cost optimal solutions for pump operating (a) Control Case B; (b) Control Case C; (c) Control Case D; (d) Control Case E

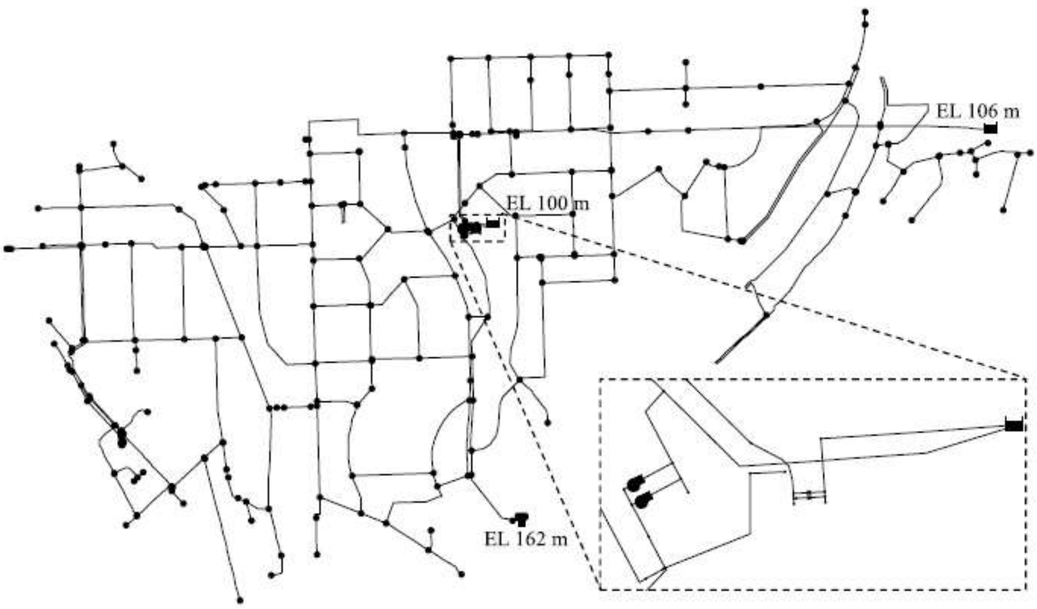

Fig. 5. South Australian network

5:35 a.m. and this allowed the tank to fill exactly for the start of the peak period [Fig. 4(b)]. During the peak period, the optimal solution started the pump at 6:20 p.m. and then shut it down at 10:20 p.m. to have the tank empty at the end of the peak period.

Control Case D: Cost Minimization

Using variable trigger levels in Control Case D found an optimal solution that maintained a low water level during the peak period, with trigger levels of 1.2 and 2.2 m, and a high water level during the off-peak period, with trigger levels of 4.4 and 5.0 m [Fig. 4(c)]. Even though this solution had a slightly greater percentage of pumping during the peak period compared with the Control Case C solution, it reduced the static head for much of the simulation period and was therefore slightly cheaper at $\$0.0649/\mathrm{m}^3$.

Control Case E: Cost and GHG Minimization

Scheduling in Control Case E was able to find solutions with reduced cost and GHG emissions compared with the other control cases. The best cost solution using VSPs used lower pump speeds throughout the off-peak period to fill the tank exactly at the start of the peak period [Fig. 4(d)] and had a cost of $\$0.0625/\mathrm{m}^3$. The use of FSPs was more expensive than VSPs; the cost optimal solution using FSP had a cost of $\$0.0656/\mathrm{m}^3$. FSP scheduling was less flexible than VSP operation and was not able to completely fill the tank for the start of the peak period. The optimal solution for GHG emissions pumped constantly throughout the day at reduced speeds, compared with the cost optimal solution, which pumped as much as possible in the off-peak period. This resulted in a cost of $\$0.0682/\mathrm{m}^3$ and GHG emissions of $0.2156\ \mathrm{kg\,CO_2\text{-}eq/m^3}$, both of which are lower than for all of the solutions (cost or GHG optimal) presented in Table 3 for Control Case A

Case Study 2: South Australian Network

The second case study was a real-life WDS in South Australia, consisting of 324 pipes, 278 nodes, two pumps (one on standby), one reservoir, and two tanks (Fig. 5). This case study was chosen to show the advantages and disadvantages of the different pump operating control cases and objectives for a real network. With only one pump operating, the comparison between the control cases could be made clearly and their effect on the objectives more easily understood. With an average daily peak day demand of 30.7 L/s compared with the pump operational flow of 126 L/s, the pump in this network was oversized and only required to operate for 8 h each day. Under the current operational regime using trigger levels of 3.96 and 5.54 m, almost half of this pumping occurred during the peak electricity tariff period (Fig. 6), when electricity rates were much higher (22 c/kWh compared with 9 c/kWh for off-peak). Cost and GHG emissions for the current operation were $\$0.0360/\mathrm{m}^3$ and $0.1460\ \mathrm{kg\,CO_2\text{-}eq/m^3}$, respectively. The maximum tank water level was 7.92 m, with a minimum tank water level set at 2.5 m, representing 30% of the full volume to account for emergency reserves and dead storage. Trigger level values considered in the optimization ranged from 4.0 to 7.9 m at an increment of 0.1 m, with the initial tank water level set at 4.0 m for all

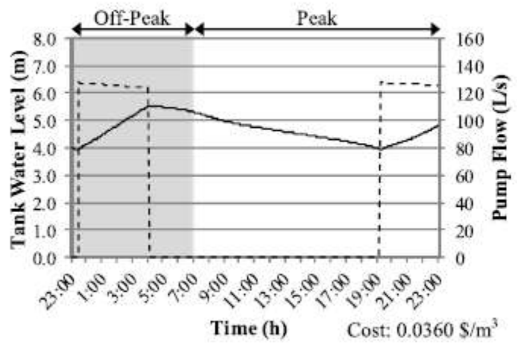

Fig. 6. Daily tank level (solid) and pump flow (dashed) variation of the South Australian network: current operation

Table 4. Optimal Solutions for Each Pump Operating Control Case for the South Australian Network

Control case	Objective	Cost ($/m^3)	Cost difference (%)[a]	GHGs (kg CO_2-eq/m^3)	GHG difference (%)[a]	Peak energy (%)	Off-peak energy (%)
A	Cost	0.0219	−39.2	0.1466	+0.4	0.0	100.0
A	GHGs	0.0438	+21.6	0.1434	−1.8	71.3	28.7
B	Cost	0.0219	−39.2	0.1464	+0.3	0.0	100.0
C	Cost	0.0219	−39.2	0.1466	+0.4	0.0	100.0
D	Cost	0.0219	−39.2	0.1466	+0.4	0.0	100.0
E	Cost	0.0218	−39.5	0.1459	−0.1	0.0	100.0
E	GHGs	0.0466	+29.3	0.1419	−2.9	80.4	19.6

[a]A negative difference indicates that the cost or GHGs in the optimal solution is less than the current operation (cost: $0.0360/m^3, GHG: 0.1460 kg CO_2-eq/m^3).

Table 5. Optimal Solutions for Each Pump Operating Control Case for the South Australian Network with a Smaller Pump

Control case	Objective	Cost ($/m^3)	Cost difference (%)[a]	GHGs (kg CO_2-eq/m^3)	GHG difference (%)[a]	Peak energy (%)	Off-peak energy (%)
A	Cost	0.0291	−19.2	0.1339	−8.3	31.0	69.0
A	GHGs	0.0385	+7.0	0.1320	−9.6	64.7	35.3
B	Cost	0.0291	−19.3	0.1339	−8.3	31.0	69.0
C	Cost	0.0291	−19.2	0.1339	−8.3	31.0	69.0
D	Cost	0.0291	−19.3	0.1139	−8.3	31.0	69.0
E	Cost	0.0280	−22.3	0.1348	−7.7	27.0	73.0
E	GHGs	0.0409	+13.4	0.1315	−10.0	72.6	27.4

[a]A negative difference indicates that the cost or GHGs in the optimal solution is less than the current operation with the original pump (cost: $0.0360/m^3, GHG: 0.1460 kg CO_2-eq/m^3).

simulations. The minimum pump speed multiplier was calculated to be 0.87 [Eq. (4) with a pump shutoff head of 92 m and maximum static head of 69.4 m], so choices for multipliers ranged from 0.88 to 1.0 in 0.04 increments (Table 2). The optimization results for all control cases for this network are presented in Tables 4 and 5 and discussed in the following sections.

Control Case A: Cost and GHG Minimization

For Control Case A, the optimal trigger levels to minimize cost for this network were 4.0 and 6.1 m, costing $0.0219/m^3, 39% less than the current operation (Table 4). The pumping in this solution occurred entirely within the off-peak period, with the tank filling between the hours of 11 p.m. and 6:30 a.m. and then draining for the rest of the day [Fig. 7(a)]. Optimizing for GHG emissions found that trigger levels of 4.0 and 4.3 m reduced emissions to 0.1434 kg CO_2-eq/m^3, a 1.8% saving on the current operation (Table 4).

Control Cases B, C, and D: Cost Minimization

With all pumping able to be completed in the off-peak period, the addition of a reduced upper trigger (Control Case B) found optimal solutions with the same cost as the optimal trigger levels solution (Control Case A). Regardless of switch time, the optimal upper trigger level was greater than 6.1 m (the optimal upper trigger level value for Control Case A), and the reduced upper trigger level varied such that all the pumping could still be achieved during the off-peak period. This indicated that it was better to pump entirely within the off-peak period with the ultimate upper trigger level in effect rather than pump throughout the day with a reduced static head. Control Cases C and D, which also attempted to take advantage of the off-peak tariff and reduce the static head during the peak period, were also not useful (Table 4). In Control Case C, the optimal scheduled pump start occurred at times when the pump was already on and the optimal pump stop when the pump was already off, leaving the operation to be entirely governed by the trigger levels, which were the same as for Control Case A. In Control Case D, the operation was governed by the off-peak lower trigger level and the peak upper trigger level, which were the same as the Case A optimal trigger levels.

Control Case E: Cost and GHG Minimization

Optimization of VSP scheduling (Control Case E) found a marginally better solution to the cost optimal trigger levels operation with a cost of $0.0218/m^3. It pumped at a reduced speed from 11 p.m. to 6 a.m. and then at full speed for the last hour of the off-peak period [Fig. 7(c)]. While the reduced speed would lead to less friction loss through the system and hence reduced energy requirements, there was an extra 90 min of pumping that meant the cost and GHG emissions from the VSP solution were very similar to the trigger levels solution (Table 4). The optimal GHG solution pumped during half of the time periods, including during the middle of the day when the emissions factors were lowest. This solution had emissions of 0.1419 kg CO_2-eq/m^3, a reduction of 2.9% compared with current operation.

Replacement with a Smaller Pump

In order to apply all of the pump operating control cases to a real-life network, the current pump was assumed to be replaced with a smaller pump that would be required to pump for more than the 8 off-peak hours each day. The current pump operated at a flow of 126 L/s at a head of approximately 70 m. Because the average demand was 30.7 L/s, a pump with a flow of approximately 40 L/s at a head of 70 m was selected. This pump required roughly 13 h of pumping per day. The shutoff head was 80 m, which gave a minimum pump speed multiplier of 0.93 and thus multipliers between 0.94 and 1.0 in increments of 0.02 were considered.

Control Case A: Cost and GHG Minimization with a Smaller Pump. Using the smaller pump in Control Case A, the optimal trigger levels for cost were 4 and 5.5 m; at $0.0291/m^3, this was more expensive than with the original pump (Table 5). This suggests that when there are large differences between the peak and off-peak cost of electricity, it may be more economical to install a larger, more

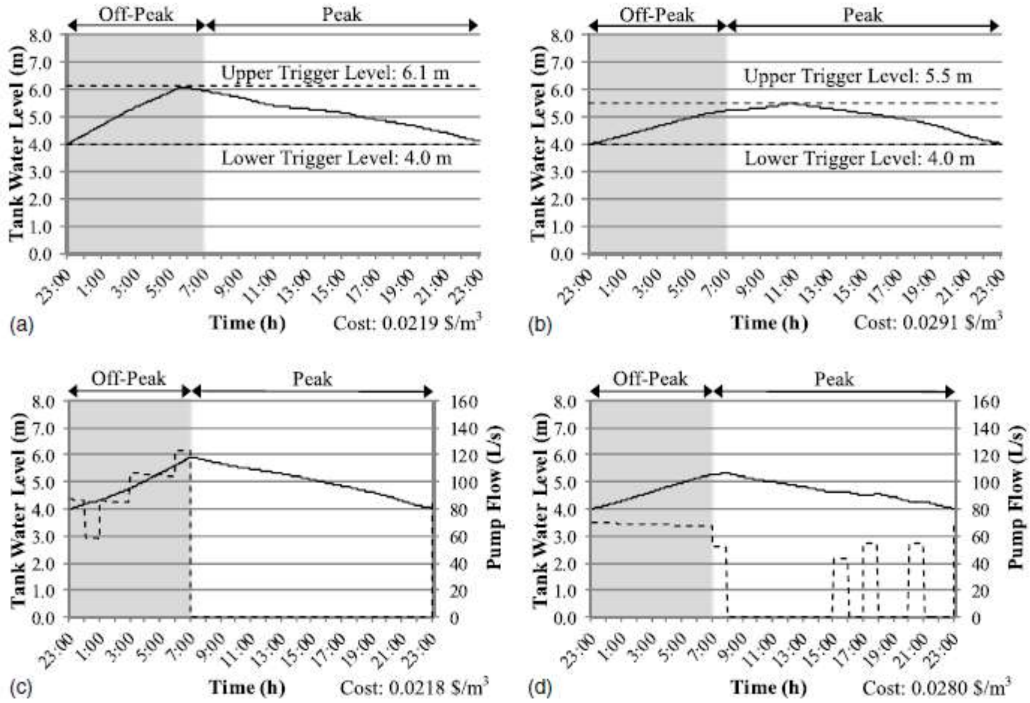

Fig. 7. Daily tank level and pump flow variation for the South Australian network: cost optimal solutions for (a) Control Case A with original pump; (b) Control Case A with smaller pump; (c) Control Case E with original pump; (d) Control Case E with smaller pump

expensive pump but have reduced operating costs by only pumping during the off-peak period. With a smaller pump, the tank did not fill as quickly and hence some of the pumping occurred during the peak period [Fig. 7(b)]. This solution still reduced the cost by 19% compared with the cost of the current operation with the original pump (Table 5). Using the smaller pump reduced both GHG emissions and cost at the same time. The cost-optimal solution for Control Case A with the original pump slightly increased GHG emissions compared with the current operation. With the smaller pump, however, the cost-optimal trigger levels also reduced GHG emissions by approximately 8%. The optimal GHG trigger levels when the smaller pump was used were 4.0 and 4.7 m, further apart than with the original pump.

Control Cases B, C, and D: Cost Minimization with a Smaller Pump. With the use of the smaller pump, Control Cases B, C, and D found optimal solutions that had effectively the same operation as for the Control Case A solution (Table 5). With a reduced upper trigger level (Control Case B), the ultimate upper trigger level was ineffective and the pump was entirely controlled by the reduced upper trigger level at an optimal level of 5.5 m. When trigger levels and scheduling were combined (Control Case C), the same optimal trigger levels were found and the scheduled pump startup occurred when the pump was already on, and similarly the pump shut down when the pump was already off. With variable trigger levels (Control Case D), the peak levels governed the operation; during the off-peak period, the tank level did not reach the off-peak upper trigger level, and the peak upper trigger level, at 5.5 m, controlled when the pump stopped.

Control Case E: Cost and GHG Minimization with a Smaller Pump. VSP scheduling (Control Case E) with the smaller pump gave a better result than the trigger level operation with a cost of $0.0280/m^3$ (Table 5); however, it was still more expensive than with the original pump because some pumping in the peak period was required [Fig. 7(d)]. The optimal GHG pump schedule with the smaller pump provided the best GHG solution for all of the South Australian network solutions in Tables 4 and 5 with emissions of 0.1315 $kg\,CO_2\text{-eq}/m^3$ giving a 10% saving on the current operation.

Conclusions

A single-objective genetic algorithm model has been developed to optimize pumping operations in water distribution systems. It was combined with a new toolkit for *EPANET2* that allowed optimization of more complex pump operating strategies than have previously been considered to be performed. Five different pump operating control cases were implemented, using various types of trigger levels, scheduling, and the combination of both. Optimization of both cost and GHG emissions were considered separately in order to compare the optimal solution characteristics of the different pump operating control cases for each of these objectives. The optimization model was applied to two different case study systems, a hypothetical one-pipe system and a real-life system from South Australia.

VSP scheduling, implemented in Control Case E, performed better in terms of both cost and GHG emissions compared with the other control cases. Generally, solutions that had a lower percentage of energy used in the peak period were cheaper; the effect of the peak and off-peak tariff was greater than the effect of reducing the static head of the system. The more complex trigger level control cases (B, C, and D) were able to improve upon the cost of

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just using lower and upper trigger levels (Control Case A) because they were able to defer more pumping to the off-peak period. Cost and GHG objectives were not always aligned because of the variation in electricity prices and emission factors.

As well as producing optimal pump operating regimes, the optimization highlighted particular features of the two case study networks and their operation. For the one-pipe network, the optimization highlighted the high demands during the evening period, which necessitated the use of a minimum tank level constraint and affected the number of decision variables used in Control Case C. The oversized pump in the South Australian network made the use of Control Cases B, C, and D redundant because all pumping could be achieved in the off-peak period. Using a smaller pump was more expensive because some peak pumping was required; however, it was able to reduce GHG emissions at the same time as reducing cost compared with the current operation. The comparison of the two pumps suggested that when there is a large difference in peak and off-peak electricity prices, it may be more economical to spend more money initially with a larger pump, and be able to pump entirely within the off-peak period to reduce ongoing costs. The model proved effective, reducing costs by almost 40% compared with the current operation of the South Australian network.

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Appendix B: Final Published Version of Publication 2 (Chapter 5)

Publication 2 presented in Chapter 5.

Framework for the Optimization of Operation and Design of Systems with Different Alternative Water Sources

Blinco, L.J., Lambert, M.F., Simpson, A.R., and Marchi, A.

School of Civil, Environmental and Mining Engineering

The University of Adelaide, Adelaide, SA 5005 Australia

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Earth Perspectives

RESEARCH ARTICLE

Open Access

Framework for the optimization of operation and design of systems with different alternative water sources

Lisa J. Blinco[1,2*], Martin F. Lambert[1,2], Angus R. Simpson[1,2] and Angela Marchi[1,2]

Abstract

Water security has become an increasing concern for many water system managers due to climate change and increased population. In order to improve the security of supply, alternative sources such as harvested stormwater, recycled wastewater and desalination are becoming more commonly used. This brings about the need for tools to analyze and optimize systems that use such sources, which are generally more complex than traditional water systems. Previous methodologies have been limited in their scope and cannot be applied to all types of water sources and systems. The framework presented in this paper has been developed for holistic analysis and optimization of water supply and distribution systems that use alternative water sources. It includes both design and operational decision variables, water and energy infrastructure, simulation of systems, analysis of constraints and objectives, as well as policies and regulations which may affect any of these factors. This framework will allow users to develop a comprehensive analysis and/or optimization of their water supply system, taking into account multiple types of water sources and consumers, the effect of their own design and operational decisions, and the impact of government policies and different energy supply options. Two case study systems illustrate the application of the framework; the first case study is a harvested stormwater system that is used to demonstrate the importance of simulation and analysis prior to optimization, the second utilizes four different water sources to increase security of supply and was optimized to reduce pump energy use.

Keywords: Water distribution systems, Integrated water resources management, Decision-making, Conceptual framework, Alternative water sources, Optimization

Introduction

A changing climate and increasing population have put a strain on traditional water resources, which typically rely on natural catchment water. This has made water security an increasing concern for many water system managers, who have investigated options for reducing demand and supplementing supply. Alternative water sources, such as harvested stormwater, recycled wastewater and desalination, are increasingly being used to improve water security of cities and towns. Methods for simulation, analysis and optimization of traditional potable water distribution systems (WDSs) cannot necessarily be directly transferred to systems that use alternative water sources. Therefore there is a need to develop a methodology specifically for alternative water source systems, which includes both hydraulic and hydrologic considerations, as well as the many additional parameters and variables associated with alternative water sources. There are many modelling tools used in current practice for integrated water management, such as eWater Source, WEAP (Water Evaluation and Planning System) and Mike Basin. These modelling tools do not include hydraulic simulation, and therefore may not accurately represent performance of urban water networks. Moreover, this framework is not software, rather its purpose is to guide water system managers in how to best simulate and optimize their systems, particularly those that integrate multiple water sources, and natural and human-made systems. The framework should be

* Correspondence: lisa.blinco@adelaide.edu.au
[1]School of Civil, Environmental and Mining Engineering, The University of Adelaide, Engineering North N136, North Terrace Campus, Adelaide, South Australia 5005, Australia
[2]Cooperative Research Centre for Water Sensitive Cities, Monash University LPO, PO BOX 8000, Clayton, Victoria 3800, Australia

used to determine which system components need to be modelled, which type of modelling tools are most appropriate, what regulations and policies need to be taken into account and how to evaluate the performance of the system.

The framework introduced in this paper can be applied to the optimization of the design and operation of water supply and distribution systems from source to consumer, considering multiple traditional and alternative sources, multiple uses and multiple objectives. Electrical energy sources and their effect on electricity prices and greenhouse gas (GHG) emissions are included, as are several types of government policies that may affect the design, operation, data and evaluation of the system. The objectives of this paper are to (1) develop a generalized framework that could be applied to any water supply and/or distribution system optimization problem and (2) outline the application of this framework to two case study systems with a focus on optimizing their operation.

Literature review

Since 2000, there has been significant consideration of the concept of water security (Cook and Bakker 2012) as water is increasingly seen as a fundamental and finite resource (Bogardi et al. 2012). Consequently, the use of alternative sources, such as harvested stormwater, desalination, recycled wastewater and rainwater, has gained traction (Fielding et al. 2015). Harvested stormwater schemes are often decentralized and used for non-potable supply such as household gardening and irrigation of public reserves (Naylor et al. 2012), however, in some cases are also used for potable supply (McArdle et al. 2011). While desalination is a climate independent (and therefore more reliable) source, is often not the most cost effective or environmentally sensitive option (Becker et al. 2010; Miller et al. 2015). Recycled wastewater is also climate independent, and generally used for large scale non-potable applications (Muga and Mihelcic 2008; Oron et al. 2014), however, it can also be used for indirect or direct potable supply (Rodriguez et al. 2009; Nagal 2015). Domestic rainwater tanks are increasing in popularity and have benefits of reducing water usage from utilities and reducing stormwater runoff from houses (Campisano and Modic 2012; Umapathi et al. 2013). Demand management strategies have also been used to reduce per capita consumption and therefore reduce the pressure on limited water supplies (Dawadi and Ahmad 2013; Friedman et al. 2014).

Some alternative sources, such as harvested stormwater, introduce additional complexity to the problem of modeling and optimization than has been previously considered for traditional water systems (Marchi et al. 2016). There is, for example, the need to consider the supply and distribution systems together, rather than separately, as it is less likely that there will be large storages isolating the supply side from the distribution side. When including the supply side, longer simulation times often need to be used, requiring rainfall and evaporation scenarios to be taken into account. The security of supply with regard to climate change needs to be considered (Paton et al. 2014; Cai et al. 2015), as some sources are climate dependent and some are climate independent. The social acceptability of using particular sources for particular applications and the willingness of consumers to pay more for alternative source systems to be constructed and maintained may need to be incorporated (Hwang et al. 2006; Londoño Cadavid and Ando 2013; Fielding et al. 2015). The perception of risks associated with alternative water source systems by water system managers may also present a barrier to the implementation and success of such systems (Dobbie and Brown 2012; West et al. 2016). Many alternative sources also have associated externalities that result in either cost or benefit to the user, such as reduced effluent flow to the ocean or receiving water body by reusing wastewater and reduced urban stream flows by harvesting stormwater (Marchi et al. 2016).

The increased use of alternative water sources then raises the question of how such systems should by analyzed and optimized to ensure they are implemented as effectively as possible. Stokes et al. (2014) developed a framework for optimizing the cost and GHG emissions of WDSs, taking into account both the design and operation of the system, energy sources and GHG emission factors. This study, however, was applicable only to traditional WDSs, with no consideration of the supply side and alternative water sources. Chung et al. (2008) developed a mathematical model for evaluating integrated water supply systems with decentralized treatments. Multiple sources, uses, transportation and treatment systems can be considered, however only surface water, groundwater and recycled wastewater sources are included. This model does not incorporate any optimization procedure, only analysis of different options developed by the user. Makropoulos et al. (2008), with further developments in Rozos and Makropoulos (2013), produced a decision-support tool for modeling the urban water system from source to tap. The software can be used to select combinations of water saving strategies and technologies, including how much water from each type of demand (for example domestic, commercial) is obtained from each source and how the system is operated. It uses a demand-oriented, water balance approach and does not include capability for other types of simulation models such as hydraulic and hydrologic modeling.

Uncertainty, particularly with regard to climate change, is an important consideration that has been taken into account in several methodologies. Paton et al. (2014) developed a framework for water supply system planning with alternative sources and climate change considerations, while Beh et al. (2014, 2015) developed two methods for optimal sequencing of urban water supply augmentation options under deep uncertainty regarding demands and climate. The research by both Paton et al. (2014) and Beh et al. (2014, 2015) considered only the planning of water supply projects, and did not optimize the specific design or operation of the systems. Sequencing is also considered in Cai et al. (2015), however, in this case it is applied to planning of drought mitigation strategies in agricultural systems. They consider multiple decision stages in which options such as infiltration ponds, parallel terraces, irrigation triggering threshold and irrigation water sources can be implemented. Marchi et al. (2016) developed a methodology for optimizing the design of harvested stormwater systems taking into account future climate scenarios; however, it does not apply to other types of alternative sources or optimization of system operation. It does include a detailed analysis of the associated externalities, such as reduced peak flows and improved economic value of properties near stormwater schemes. Ashbolt et al. (2014) introduced a framework for planning of short-term operations for water systems using surface water, groundwater, desalination, and recycled wastewater with multiple objectives and multiple inflow replicates to account for uncertainty. Long-term operating strategies and the design of the system were not included and the operating strategies considered were limited to bulk water transfers and not the operation of pumps and smaller storages.

Framework for the optimization of alternative water source systems

The framework presented in the current paper was developed to guide the modeling and optimization of water supply and distribution systems that use alternative water sources. It is comprised of several components and sub-components that fit within an optimization structure, for example, a multi-objective evolutionary algorithm (Fig. 1). The options component [OPT] describes the potential 'decision variables' that are available in an optimization problem, that is, the factors that can be changed in order to produce a different outcome. This includes both the initial design of the water supply and distribution infrastructure and the long- and short-term rules that govern the operation of the system once it has been commissioned. The infrastructure component [INF] describes the physical components of the system that need to be modeled and the

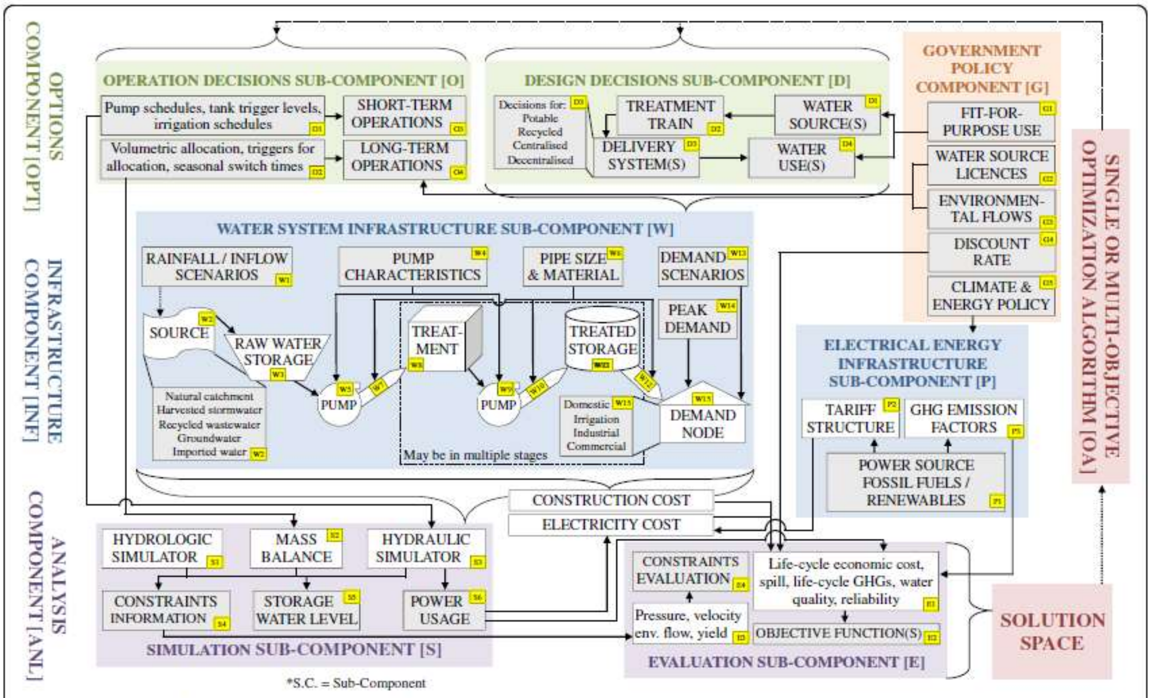

Fig. 1 Schematic of the framework for optimizing the design and operation of alternative water source systems

data associated with each, including both water infrastructure and energy infrastructure, which may affect the evaluation of electrical energy cost and life-cycle GHG emissions. There is also a government policy component [G] that covers the policies from regulating bodies that may affect other aspects of the framework. The analysis component [ANL] describes the simulation of each potential system configuration and evaluation against objectives and constraints. The optimization algorithm [OA] investigates different possible combinations of decision variables from the options component, models the system according to the infrastructure component and evaluates it using the analysis component to find the optimal solution(s).

Details of the components and sub-components are shown in Fig. 1 and described in Sections 'Options component [OPT]', 'Infrastructure component [INF]', 'Government policy component [G]' and 'Analysis component [ANL]'. Table 1 summarizes the parameters that need to be considered in the optimization and simulation of alternative water source systems with respect to the different items that are presented in Fig. 1 and in the following sections. There are three (non-exclusive) categories that each parameter may be placed in – decision variables, parameters that are set, and uncertain parameters. Decision variables are parameters that the user may be able to examine using optimization. It is important to note that in most optimization problems, not all of these parameters will be available as decision variables at once, and it is likely that only a small number will be considered. For example, when optimizing pump operations for an irrigation system, only the first three 'decision variables' shown in Table 1 (pump schedules, tank trigger levels, and demand scheduling) may be considered. The remaining parameters that are designated as decision variables in Table 1, particularly those relating to the design of the system (for example, delivery system layout and pump sizing) would already be set and not able to be optimized if the existing infrastructure cannot be modified. The parameters that are set are those that very rarely, if ever, are able to be optimized by the user. These include parameters that would be controlled by external sources, for example consumers of domestic or commercial demands, pipe manufacturers and higher level government and regulatory bodies; and also parameters that need to be predefined to a known or assumed value before optimization or simulation can be performed, for example, fire demand/reserve, hydrologic/hydraulic variables and objective and constraint selection and definition. The final category, uncertainty, designates those externally set or predefined variables that are not well known or may be subject to change in the future and therefore may need to be considered in a sensitivity analysis. While the selected values of decision variables have an impact on the performance of a system, they are generally within the control of the decision maker, and therefore are not classed as 'uncertain'. It is important to note that the categorization in this table is indented as an indication of how each parameter is typically treated. There are, of course, exceptions to this, as almost all of the parameters could be considered as decision variables if desired and have some associated uncertainty. For example, environmental flows have been designated as an externally set parameter, as it is likely that the operator of a system will have to meet requirements set by an external organization such as the Environmental Protection Agency. They may, however, want to investigate providing greater environmental flows, or show the benefits of reducing their environmental flow requirements and being able to supply more water elsewhere.

Options component [OPT]

The options component covers the potential decision variables (and the range of possible choices for the decision variables) for an optimization problem. This component is split into two sub-components; the operational decisions sub-component [O] and the design decisions sub-component [D]. Design decisions include elements that can be changed before a system is constructed, such as the layout and capacities, materials and other properties of the various infrastructure components. Operational decisions include elements that can be changed after construction during the daily management of the system, such as the operating rules for pumps and valves and allocation of water from different sources.

Operational decisions Sub-component [O]

Both short- and long-term operations are considered in the operational decisions sub-component. The critical aspects of this sub-component (items in **bold** can be optimized), as shown in Fig. 1 and Table 1 are:

- [O1] the specific short term operating strategies including **pump schedules** (when pumps are turned on or off based on time), **trigger levels** (water levels in tanks or other storages that determine when pumps or valves turn on or off), **irrigation or demand schedules** (for systems where they can be pre-determined), **valve settings and operating rules**, and **pressure settings for pumps** (to maintain the set pressure at a particular point).
- [O2] the specific long term operating strategies including **volumetric allocation of water** from different alternative sources, **trigger levels** (for example in reservoirs) that determine allocations from different sources or water demand restriction levels, **switch**

Table 1 Summary of parameters for the design and operation of alternative water source systems

Parameter	Decision variable[a]	Parameter that is set	Uncertain parameter	Relevant items in Fig. 1
Operational inputs [O]				
Pump schedule	X			O1
Tank trigger levels	X			O1
Tank/storage maximum and minimum allowable levels		X		O1, W3, W11
Demand pattern (irrigation, agriculture)	X			O1, D4, W13
Demand pattern (domestic, commercial, industrial)		X	X	O1, D4, W13
Demand flow rate (peak, average, peak day)		X	X	O1, D4, W14
Valve settings or operating rules	X			O1
Pump pressure settings	X			O1
Volumetric allocation of water	X			O2
Reservoir trigger levels	X			O2
Switch time between operating regimes	X			O2
Priority ranking of operating rules		X		O3, O4
Design inputs [D] and water infrastructure [W]				
Water source selection	X			D1, W2
Water source infrastructure (layout, capacity)	X			D1, W2
Treatment type selection	X			D2, W8
Treatment infrastructure (layout, capacity, treatment rate/level)	X			D2, W8
Delivery system type selection	X			D3
Delivery system layout (lengths, elevations, junctions, tank locations)	X			D3, W7, W10, W12, W15
Pipe material and diameters	X			D3, W7, W10, W12
Pipe parameters (unit cost, pipe wall roughness (ε), wall thickness, embodied energy)		X	X (ε)	D3, W6, W7, W10, W12
Pump sizing	X			D3, W5, W9
Pump performance characteristics and cost		X		D3, W4
Tank sizing (capacity, height, diameter)	X			D3, W3, W11
Fire demand/reserve		X		D3, W11
Water user type selection	X			D4
Rainfall/streamflow series		X	X	W1
Reservoir capacity and volume curve	X			W3
Pond (e.g. wetland) capacity and volume curve	X			W3
Prioritization rules for demands types		X		W15
Other inputs [P], [G] and [S]				
Power source selection		X	X	P1, P3, G5
Electricity tariff structure and cost		X	X	P2
GHG emission factors		X	X	P3, G5
Fit-for-purpose requirements		X		G1
Water license amounts		X		G2
Environmental flow amounts		X		G3
Discount rate		X	X	G4
Hydrologic variables (e.g. permeability)		X		S1
Hydraulic variables (e.g. water temperature)		X		S3

Table 1 Summary of parameters for the design and operation of alternative water source systems *(Continued)*

Optimization problem formulation [E]		
Objective selection	X	E1
Objective function(s)	X	E2
Constraint selection	X	E3
Constraint limits (maximum and minimum)	X	E4
Penalty costs	X	E4

[a]Note: Parameters specified as decision variables are shown in bold throughout Sections 'Options component [OPT]' and 'Infrastructure component [INF]'

times between different operating regimes (for example between different trigger level sets for different seasons) and power source selection.

[O3] the overall short-term operating strategy, including operating rules that are optimized in [O1] and operating rules that are pre-set and are not to be optimized (acting as constraints). Where there are multiple operating rules, the priority of each rule and order they are enforced in is important to consider.

[O4] the overall long-term operating strategy, including operating rules that are optimized in [O2] and operating rules that are pre-set and are not to be optimized. Again, the priority and order of the rules is important to consider.

Most systems have multiple operating conditions to meet and therefore multiple operating rules will be in place. Prioritization of the different operating rules is important, and this may be set by the operator or be chosen by the optimization tool. This component requires information from the government policy sub-component ([G] in Fig. 1), specifically in terms of water source licensing and environmental flow regulations. These policies would typically be regulated by local or state government departments or the environmental protection authority. Operational rules set in this sub-component will inform the simulation sub-component [S] as they will need to be represented in any simulation model(s) of the system.

Design decisions Sub-component [D]

This sub-component incorporates all of the design decisions that are available to the designer for the entire water supply and distribution system, from source to user. The critical aspects of this sub-component (items in **bold** can be optimized), as shown in Fig. 1 and Table 1 are:

[D1] the **water sources selected** to be used including natural catchments, harvested stormwater, recycled wastewater, groundwater, imported water, domestic rainwater, desalination, domestic greywater and sewer mining; and the **layout and capacity of source infrastructure**.

[D2] the **types of treatment selected** including centralized treatment at plants such as mechanical filtration, chemical dosing, ultraviolet treatment and ozonation, and decentralized in situ treatments such as gross pollutant traps, wetlands and biofilters; and the **layout, capacity, dosing rates and retention times for treatment facilities**.

[D3] the **type and configuration of the delivery system** used including potable, non-potable (for example dual reticulation systems to deliver recycled water), centralized and decentralized, and the infrastructure design variables such as **system layout, pipe sizes, lengths and materials, pump sizing, valve sizing, and tank sizing**.

[D4] the **types of water users** that are supplied by the system including potable, irrigation, agriculture, industrial, non-potable domestic/commercial and firefighting, and the demand rate and pattern for water use (for example, scheduling of irrigation demands).

Regulations on fit-for-purpose water use from the government policy component [G] in Fig. 1 inform what water sources can be used for particular applications and these are likely to be specified by state or federal government departments or health authorities. Generally, sources such as harvested stormwater and recycled wastewater cannot be used for potable supply and rather serve non-potable demands in dual-reticulation systems or are supplied to irrigation, agricultural and industrial users. There may be some systems, however, in which necessary approvals have been obtained to use these sources for potable supply. The design decisions are inputs to the water system infrastructure sub-component [W] which describes the system elements and data to be modeled.

Infrastructure component [INF]

The purpose of this component is to describe the infrastructure that needs to be modeled in order to evaluate the objectives and constraints of the problem. There are two sub-components; the water system infrastructure sub-component [W] and the electrical energy infrastructure sub-component [P]. Water system infrastructure includes the specific aspects of the water supply and distribution system and the data required, including construction and maintenance costs. Electrical energy infrastructure includes the power source (fossil fuel types and renewable types) and the electricity price and GHG emission factor data needed.

Water system infrastructure Sub-component [W]

This sub-component includes the specific infrastructure aspects of the water system design and the relevant data that is needed in order to simulate it. Most systems and optimization problems will not require all of these factors to be considered or modeled; however, the purpose of this framework is to cover a large range of the possible requirements for an optimization and hence the scope is intentionally broad.

The water system infrastructure sub-component [W] as shown in Fig. 1 represents a system with one water source, one treatment plant, one storage tank and one demand node. In reality, many systems will have more than one of each of these components, particularly the treated storage [W11] and demand node [W15]. Pumping of water between storages may occur in multiple stages, particularly when there is a large difference in elevation. For typical centralized potable WDSs, all treatment will occur at one water treatment plant. In decentralized systems such as for harvested stormwater schemes, however, treatment may occur in multiple stages. For example, a gross pollutant trap may be located on an urban creek before the water is collected in a harvest pond, then the water may be pumped to be treated through a wetland, and then treated again in a treatment plant.

The critical aspects of this sub-component (items in **bold** can be optimized) as shown in Fig. 1 and Table 1 are:

[W1] the rainfall or inflow scenarios for the water source; for example rainfall or streamflow scenarios for natural catchments and stormwater sources, or a sewer system flow pattern for recycled wastewater. Sources such as desalination and, depending on the temporal scale of the optimization, groundwater, do not usually require an inflow scenario. Rainfall and streamflow scenarios may be a data series obtained from measurements at gauging stations or modeled in a hydrologic simulation program [S1]. Multiple inflow scenarios may be used, particularly for systems with highly variable inflows. Losses such as evaporation and infiltration may also need to be taken into account for sources with large open storages such as reservoirs and natural water ways.

[W2] the **source type** as described in [D1] with input from [W1].

[W3] the raw water storage; this may be a reservoir (typical for a natural catchment), a harvest pond for a stormwater system, a tank (for example for a recycled wastewater system) or an aquifer for groundwater. Associated data including **capacity, a volume curve, elevation, height and diameter** is required.

[W4] characteristics of available pumps such as performance curves (head, efficiency, and power against flow), cost, rated speed and variable speed pump (VSP) information where applicable.

[W5] the **pump** transferring water from the raw water storage to a treatment facility, requiring data from [W4].

[W6] pipe size and material information such as available diameters, unit costs, pipe wall roughness, wall thickness and embodied energy. For new pipes, this information will be easily obtained from the pipe manufacturer. For existing systems, however, there may be some uncertainty in these parameters if detailed records of the 'as constructed' system and any pipe replacements have not been kept. In addition to this, the pipe wall roughness of existing pipes will generally be uncertain. Pipe wall roughness increase as pipes age, and pipe condition assessment may be needed to provide an estimate.

[W7] the **pipe system** transferring water from the raw water storage to the treatment facility, **pipe lengths and layouts** need to be known as well as information from [W6].

[W8] the **treatment facility** that will produce water of the required quality based on the source type and demand type. Characteristics of the individual treatment methods as described in [D2] need to be known.

[W9] the **pump** transferring water to a treated storage, requiring the same data as [W5].

[W10] the **pipe system** transferring water to a treated storage, with the same information as [W7] required.

[W11] the **treated storage**, for example, a tank or multiple tanks that are typically at a high elevation point of the network in order to supply demands by gravity. Data required includes the **elevation, height, diameter** and maximum and minimum allowable water levels.

[W12] the **pipe system** transferring water from the treated storage to consumers, which again requires information as in [W7]. This pipe system is likely to be more complex than those in [W7] and [W10], particularly for systems with many different demand nodes. For systems with only one source of water, [W7] and [W10] are likely to be single pipelines. For decentralized systems with only one specific consumer, [W12] will also most likely be a single pipeline. Most systems, however, have much more than one demand point and as such distribution systems are often looped or branched systems that require more complex analysis than single pipelines.

[W13] demand scenarios that will be applied to the demand nodes, consisting of a pattern of demand multipliers over a day, week or year. There may be multiple demand scenarios required for a system, for example, if there are different types of demand nodes (such as domestic, commercial, industrial) or different seasonal demands.

[W14] the peak demand is the demand rate that is typically used to size the system components and so will affect the design of the system. The demand scenarios [W13] are more likely to affect the operation of the system as the demand varies over the simulation time. The peak day demand (average demand over the peak day), the peak hour demand (the average demand over the hour with maximum consumption in the peak day) and average demand rates may also be required. Fire loading demands and other emergency conditions will affect the design of the system, for example storage tanks should be sized to be able to provide demand in the case of fires, other emergencies and system failures (e.g. if the supply to the tank is cut off).

[W15] the demand nodes for the consumers, these may be different types of users as described in [D4] and require information from [W13] and [W14]. Different types of users will have different demand rates [W14] and demand patterns [W13]. When simulating the system, an average demand rate will often be used with the demand pattern, rather than the peak demand. Systems with multiple demand nodes may prioritize different types of demands over other, for example, irrigation systems using non-potable water may prioritize high profile sport fields over reserves with no formal usage.

Choices made in the optimization of the design decisions sub-component [D] in Fig. 1 will be inputs to the water system infrastructure sub-component. There may be other parameters that are not decision variables in the optimization (as differentiated in Table 1) though are still required by this sub-component in order to simulate the system. The construction and maintenance costs of each of the infrastructure components needs to be known in order to calculate the initial construction cost and ongoing costs as part of life-cycle economic costing. Information collected through this sub-component will be input to the simulation sub-component [S] depending on the types of simulation models used and to the evaluation sub-component [E] through the construction cost or other factors calculated for the specific objectives of a problem.

Electrical energy infrastructure Sub-component [P]

The electrical energy infrastructure sub-component includes any power infrastructure that affects the electricity prices and GHG emission factors. The critical aspects of this sub-component as shown in Fig. 1 and Table 1 are:

[P1] the breakdown of power sources including fossil fuel sources such as coal and oil, and renewable sources such as solar, wind and hydrothermal.

[P2] the electricity price tariff structure, which may be a peak and off-peak structure, or multi-part (more than two price levels) and could include a peak demand charge which applies to the peak electricity power usage in each month.

[P3] the GHG emission factor, which is based on the power source breakdown [P1] and may vary with time, either in the short-term (with sources that do not have storage such as solar panels and wind turbines) or the long-term (as fossil fuel sources tend to be phased out and renewable sources become more popular).

Climate and energy policy [G5] in the government policy component in Fig. 1 will affect the power source breakdown and electrical energy pricing now and into the future. This is likely to be regulated by a federal government department or body. Information from this sub-component is used to calculate electrical energy costs in order to evaluate life-cycle economic costs and also to calculate life-cycle GHG emissions in the evaluation sub-component [E].

Government policy component [G]

The government policy component covers policies by regulating bodies at any level (local, state, federal) that may affect other aspects of the framework. These policies need to be considered over the operational life-span of the system, for example, climate and energy policy may affect future energy sources and therefore affect future GHG emissions. The critical aspects of this component as shown in Fig. 1 and Table 1 are:

[G1] fit-for-purpose water use, which may be regulated by state or federal governments or health agencies and affects which water sources [D1] and water uses [D4] can be combined in the design decisions sub-component. It may also guide which design decisions (for example, treatment) are appropriate.

[G2] water source licenses, which may be regulated by local or state governments or the environmental protection agency, depending on the catchment size, and will affect the amount of water available from particular sources for allocation in long-term operations [O4].

[G3] environmental flows, which similarly to water source licenses may be regulated by local or state bodies depending on the size of the catchment and affect the amount of water available for allocations [O4].

[G4] the discount rate applied to operational costs and GHG emissions in life-cycle analysis [E1]. This is unlikely to be set by a government body and rather will be informed from outside the decision making team, generally by recommendations from economists.

[G5] climate and energy policy set by state and federal governments will affect the energy sources available now and in the future, therefore affecting GHG emission factors and any GHG objectives [P].

Analysis component [ANL]

The analysis component uses information from the options, infrastructure and government policy components to simulate the system and evaluate how it performs relative to the objectives and constraints. Within an optimization algorithm, the analysis component is used to assess multiple combinations of decision variables from the options component to determine how they perform. There are two sub-components within the analysis component; the simulation sub-component [S] and the evaluation sub-component [E]. The simulation sub-component includes the modeling aspects of the problem and the key variables that are required to be output from the models in order to evaluate the system. Optimization objectives and constraints are defined in the evaluation sub-component, which also provides information to the optimization algorithm as to which of the potential solutions perform best.

Simulation Sub-component [S]

The simulation sub-component considers the type of simulation model that is most applicable to the particular system and problem, and specifies the key variables that need to be calculated in the model(s). The critical aspects of this sub-component as shown in Fig. 1 and Table 1 are:

[S1] the hydrologic simulator, which is required if rainfall scenarios need to be transformed to streamflow, typically for systems using natural catchment water or harvested stormwater.

[S2] the mass balance model, which may be required for systems that have multiple water sources with long-term allocation decisions, particularly if there are different rainfall and evaporation scenarios to be considered for the storages.

[S3] the WDS hydraulic simulator, which is required to analyze pump and pipe systems that transfer water between different storages and treatments and to consumers.

[S4] information on constraints, such as yield from a hydrologic model, environmental releases and system reliability from a mass balance model, and nodal pressures, pipe velocities, pump switches and tank levels from a hydraulic model.

[S5] the water levels in storages, which are important particularly when considering operational decisions, such as trigger levels, and for constraints, such as system reliability.

[S6] the power usage from any pumps or treatment facilities, which are important in informing the ongoing electrical energy costs as part of life-cycle economic costing. Generally a WDS hydraulic simulator is required to model detailed pump operations and therefore accurately estimate the pump power usage.

Each of the three types of models will require different simplifications or assumptions depending on the particular system. For example, mass balance modeling will generally only consider one pump operating point so may not accurately calculate the pump power usage. When deciding which type of model to use for a particular problem, the user will need to consider the different simplifications, assumptions, advantages and disadvantages of each model. Trade-offs between accuracy of outputs and simulation run times need to be considered. For example, when optimizing both short- and long-term operations of a system, there is likely to be a trade-off between using a hydraulic simulator for detailed hydraulic information and using a mass balance model for shorter run times. Most problems may ideally use elements from more than one type of model; however, using multiple models will increase computational complexity and run times. Wherever possible, the most applicable type of model should be selected and augmented with the required elements from other types of models. Depending on the particular system and optimization problem, there may be other key variables that need to be calculated in the simulation models. For optimization of pumping operations, which is the focus of the case studies in this paper, storage water levels and pump power usage are the most important. Existing hydrologic, mass balance and hydraulic simulators, for example, MUSIC, WATHNET and EPANET, have often been used in conjunction with optimization algorithms and should be taken advantage of where possible rather than creating individual simulators for different problems.

Information from the operation decisions sub-component [O] will be input to the simulation sub-component as the overall operating strategy for the system ([O3] and [O4]) will need to be modeled. Short-term operations are likely to be considered in a hydraulic simulator and long-term operations, including allocations, in a mass balance model. Parameter data on the physical components of the system from the water system infrastructure sub-component [W] are also required as inputs for this sub-component. Constraint information is provided to the evaluation sub-component to compare the systems performance against specified requirements. Energy usage is used to calculate objective functions such as life-cycle economic costs and life-cycle GHG emissions. Simulating systems prior to optimization is an important step to help inform the formulation of the optimization problem and provide a check that results from the optimization are reasonable.

Evaluation Sub-component [E]

The purpose of the evaluation sub-component is to compare the performance of each of the potential solutions to the objectives and constraints of the problem. The critical aspects of this sub-component as shown in Fig. 1 and Table 1 are:

[E1] the specific objective(s) to be considered in the optimization; typically, minimizing life-cycle economic cost is a primary objective (or a component of that such as construction cost or operational cost individually). Other possible objectives include minimizing spills from reservoirs and other storages, minimizing life-cycle GHG emissions (or a component of that such as embodied energy from construction or operational emissions), minimizing supplemental potable water supply (in systems using non-potable sources), maximizing water quality, maximizing reliability and minimizing environmental impact.

[E2] the objective function(s) to be optimized; multiple objectives may be evaluated as individual functions in a multi-objective optimization algorithm or combined into a single function for use in a single objective optimization algorithm. It is important to consider how each objective should be formulated, for example, when optimizing short-term pump operations to minimize ongoing costs, the objective function may be evaluated in terms of cost per volume of water pumped, as this will take into account the amount of water delivered to consumers. Reliability of a system may be formulated in different ways, for example minimizing the time spent with water restrictions applied or minimizing the time spent below a certain storage level. Some objectives may be more difficult to quantify, such as minimizing environmental impact, so more specific objectives may be required, for example, maximizing environmental flow or minimizing the change in a water body's natural hydrological regime. Simplifications and assumptions may be required to formulate some objectives as mathematical functions. When performing multi-objective optimization, trade-offs between the different objectives should be considered by the development of Pareto fronts, allowing the decision maker to determine which Pareto optimal solution best fits their needs (see examples in Wu et al. 2010a, b, 2012a, b, 2013).

[E3] the specific constraints to be considered as described in [S4].

[E4] the evaluation of the constraints compared to the limits set by the user; maximum and/or minimum values for each constraint need to be specified. Some constraints may be flexible, for example, if an environmental flow is set by a regulator, the operator could consider increasing the set environmental flow as a decision variable in the optimization. There are several different ways constraints can be incorporated into the optimization algorithm. Penalty functions are often used for single-objective problems. They add value (often a monetary amount) to the objective function in a minimization problem and remove value from the objective function in a maximization problem based on the magnitude of the constraint violation, therefore making solutions that violate constraints less desirable (Nicklow et al. 2010). Care must be taken when formulating penalty functions to keep solutions that only slightly violate constraints in consideration during the optimization process, while ensuring the feasibility of the final optimal solutions. For multi-objective problems, a constraint-handling technique that will ensure feasible solutions are retained in preference to infeasible solution is often employed. An example of this is the constraint tournament selection procedure introduced by Deb et al. (2002).

Information about the objectives is received from the simulation sub-component [S] and from the calculation of construction, maintenance and electrical energy costs based on the water system infrastructure sub-component [W] and simulation sub-component. A discount rate for costs or GHG emissions may be set in the government policy sub-component [G] which will impact the ongoing costs and emissions in a life-cycle analysis. The discount rate may be informed by economists, such as the Stern review which recommends low discount rates for projects that lead to the production of GHG emissions (Stern 2006). Information about the performance of each potential solution in relation to the objectives and constraints is provided to the optimization algorithm in order to find the best solutions.

Optimization algorithm [OA]

The optimization algorithm is used to determine which solution(s), out of many potential solutions to the problem, performs best in relation to the objective function(s). The procedure used to set up the optimization will depend on the type of algorithm chosen; however, the first step is generally to define the decision variables, objectives and constraints of the problem. This will then guide what aspects of the system need to be modeled and what data is required in order to take into account all of the decision variables and that will provide information for all of the objectives and constraints. Multiple potential solutions to the problem form the 'solution space' and the optimization algorithm guides the search of this solution space towards the global optimum. The size of the solution space depends on the number of decision variables and number of choices available for those decision variables. More complex problems are often described as having a more 'rugged' solution space, meaning the optimization algorithm is more likely to get trapped in local optima and will have more difficulty finding the global optimum. When a single objective optimization algorithm is used, one optimal solution will be found, while in multi-objective optimization, a Pareto front will be developed with multiple solutions representing different trade-offs between the objectives.

Most optimization algorithms have parameters that need to be defined by the user, such as the number of generations or iterations and the population size in evolutionary algorithms. Although the choice of these parameters does not influence the components shown in Fig. 1, they have an effect on the optimal solutions found by the algorithm. In general, the most effective set of parameter values to use will vary between different optimization problems and the size of the solution space can only give some indication of what parameter values to use. In fact, multiple parameter sets should be tested in order to find the most appropriate values for the specific problem. Ideally, the chosen parameter set should find the same optimal solution regardless of the starting point or initial solution(s) for the optimization. Dandy et al. (1996) presented an improved genetic algorithm formulation for optimization of WDS design. Five different parameter sets were trialed on both their improved genetic algorithm and a comparatively simple genetic algorithm. They acknowledged that parameter selection does require some judgement on the part of the user, however, they found their optimization results to be relatively insensitive to the parameter choice, particularly for the improved genetic algorithm. As well as the effect of various parameter values, different optimization algorithms will be more suited to different problems. This issue has been addressed by the development of hybrid algorithms, such as AMALGAM (a multi-algorithm, genetically adaptive multiobjective approach proposed by Vrugt and Robinson (2007)), which combines several different optimization algorithms to improve search efficiency. These hybrid algorithms also have the benefit of requiring little to no parameter specification by the user.

Sensitivity analysis

As identified in Table 1, values of some input parameters (for example, describing the network or water demand loadings) are uncertain or subject to change in the future. Sensitivity analysis can be performed to account for a wide range of possible future conditions when optimizing and simulating systems. Variation of a particular parameter may result in different Pareto fronts (in multi-objective optimization) or different optimal solutions (in single objective optimization), as seen in Wu et al. (2010b) when they considered variations in discount rates. These various Pareto fronts or optimal solutions along with the various parameter values that produced them can then be provided to the decision maker. Sensitivity analysis will also help to identify if there are any uncertain parameters that do not affect the optimal results. Robustness of the optimized solutions can also be explored *a-posteriori*: in general, solutions that perform well for many different possible conditions are more desirable from the decision makers' point of view. Climate change provides an additional source of uncertainty for the parameters identified in Table 1 – detailed discussion of this is omitted from Sections 'Demand', 'Rainfall and streamflow', 'Electricity and GHG emissions' and 'Discount rate' as it is covered in Section 'Climate change'.

Demand

In some applications, such as irrigation and agriculture, the demand rate and pattern may be deterministic [O1], either the water supplier has control over the consumption, or may be able to work with those who do to determine an optimal demand schedule. For other applications, such as domestic, commercial and industrial, the demand rate and pattern depends on the consumption of water by multiple individual users

[D4, W13, W14, W15], and therefore has greater uncertainty. Historical consumption can provide some level of assurance as to how water may be used in the future, at least on an aggregated scale. Diurnal, weekly and seasonal demand variations need to be considered. In the future, factors such as climate change, population growth and water saving initiatives will affect how water is consumed and therefore impact demand rates and patterns. Emergency conditions and system failure are by their nature unpredictable and this should be taken into account when designing and operating WDSs.

An example of how demand uncertainty can be considered in the optimization of WDS design is the study by Basupi and Kapelan (2015). The demand at each time step was based on a normal distribution with a gradually increasing mean (based on deterministic demand forecasts) and an increasing standard deviation. Monte Carlo or Latin Hypercube simulation was included in their methodology to consider multiple demand scenarios. Each solution in the Pareto front was also further analyzed against three demand projections – average, optimistic (low overall demand) and pessimistic (high overall demand). Their results demonstrated the value of flexible WDS design over deterministic approaches when considering uncertainty.

Rainfall and streamflow

Rainfall and streamflow inputs [W1] may be required for systems using natural catchment water, harvested stormwater or imported water, and they are often treated with higher uncertainty than demands (Seifi and Hipel 2001; Reis et al. 2005). Within the current climate, there may be multiple realizations of possible rainfall and streamflow series (for example dry or wet years). Beh et al. (2015) considered rainfall, as well as population and temperature, as uncertain variables in their optimal sequencing methodology for water supply system augmentation. They considered both climate and hydrologic variability: seven possible future climate scenarios provided different forecasted rainfall reductions, and within each of these seven scenarios, 20 stochastic replicates of the rainfall sequence were produced. Different Pareto fronts were produced for each climate scenario, with the more severe scenarios finding solutions that required greater system augmentation and therefore had higher costs and GHG emissions. The robustness of each Pareto solution was calculated based on the average reliability and vulnerability of the solution over the 20 rainfall sequences for the particular climate scenario.

Electricity and GHG emissions

Power source(s) [P1], electricity tariffs and costs [P2] and GHG emission factors [P3] will generally be known for the present time, however, it may not be clear how they will change in the future. The mix of power sources changes naturally over time, as different power plants are built or decommissioned. This change in power source types over time, as well as technical advancements will affect the cost and GHG emissions associated with electrical energy generation. The electricity market and economic factors will also affect the cost of electrical energy over time. Changes in electricity and GHG emissions can be an important factor to consider during an optimization problem, as shown in the following examples. Blinco et al. (2014) studied the optimization of pump operations in WDSs in relation to the minimization of GHG emissions and the use of different power source scenarios, showing that optimal tank trigger levels can be influenced by the variation in emission factors. Wu et al. (2012a) considered three different electricity tariff scenarios, which increased over time, and three different GHG emission factor scenarios, which decreased over time, in the optimization of WDS design. The different electricity tariff and emission factor scenarios affected the solutions found in the Pareto front and their overall costs and GHG emissions.

Discount rate

A discount rate [G4] may be used in life-cycle analysis for both ongoing economic costs and ongoing GHG emissions. In practice, discount rates on economic costs vary significantly between different organizations, generally from 2 to 10% (Rambaud and Torrecillas 2005), while many water utilities use discount rates in the range of 6 to 8% (Wu et al. 2010a). When selecting discount rates, consideration should be given to whether both economic costs and GHG emissions are discounted, if they have the same discount rate, and if intergenerational equity is taken into account using social discount rates. Various social discount rates have been proposed for discounting ongoing costs; the Intergovernmental Panel on Climate Change (IPCC) adopted a zero discount rate over a period of 100 years, after which no consideration for future costs or benefits is given (Fearnside 2002), other suggestions include 1.4% (Stern 2006) for projects that are impacted by climate change, 2–4% (Weitzman 2007) and a time declining rate (Gollier and Weitzman 2010). Wu et al. (2010b) gave an example of a sensitivity analysis of discount rates in the optimization of WDS design for minimization of costs and GHG emissions. Discount rates of 0, 1.4, 2, 4, 6, 8% and a time declining rate were applied to the economic costs, with GHG emissions either not discounted at all, or discounted at the same rate as costs. They found that the different discount rate scenarios produced different Pareto fronts; when GHG emissions were discounted, the solutions tended to have lower capital costs and higher operating emissions.

Climate change

Management of water resources in the developed world has been based on an assumption of stationarity – that is, 'that natural systems fluctuate within an unchanging envelope of variability' (Milly et al. 2008). The effects of human-induced climate change make this assumption no longer valid (Milly et al. 2008), and introduce additional sources of uncertainty for many parameters. Uncertainty introduced by climate change is twofold – firstly, the impacts of climate change increase the uncertainty of future weather conditions; and secondly, our response to the threat of climate change and the types of adaption methods that will be utilized in the future are uncertain. Climate change affects the magnitude and temporal and spatial distribution of rainfall, temperature and other environmental factors, thus the possible rainfall and streamflow series to consider for the future will likely be different to the present. Changes to temperature and other environmental factors will also affect the hydrology of natural and urban catchments and therefore change how rainfall will transform to runoff or streamflow. Climate change impacts will also affect how people consume water, for example, higher temperatures and lower rainfall may drive people to water their gardens more. In order to simulate future climate conditions, general circulation models (GCMs) are often used in conjunction with future emissions scenarios. According to Mpelasoka and Chiew (2009), 'GCMs are the best tools available for simulating global and regional climate systems', however, the information provided is generally too coarse for applications to catchment runoff, and therefore some kind of downscaling is required. The modeling uncertainty of both the GCMs and downscaling methods increases the uncertainty of future climate scenarios (Paton et al. 2013). In 2000, the IPCC introduced several emissions scenarios (termed SRES scenarios) projecting future global GHG emissions (IPCC 2000). The various scenarios are based on different assumptions of the mix of energy generating technologies (fossil fuel or non-fossil fuel dominant) and population, economic and technological growth (IPCC 2007).

The extent to which we can reduce our GHG emissions will affect the magnitude of climate change impacts on rainfall and temperature. With the growing concerns of climate change and sustainability, renewable sources such as solar and wind will become more prevalent and replace fossil fuel sources such as coal and gas. This may affect electricity pricing and GHG emissions from power generation. Multiple future power source scenarios assuming different levels of climate change mitigation may need to be considered. Other climate change adaption strategies include economic incentives such as carbon taxes and cap and trade systems, which may affect economic analysis of WDSs. As discussed in Section 'Discount rate', when climate change and intergenerational equity are considered, social discount rates of 0, 1.4, 2–4% and time declining rates have been proposed.

Paton et al. (2013) analyzed the sources of uncertainty relating to climate change and their impact on water supply security. They considered 19 different scenarios with different combinations of six SRES scenarios, seven GCMs and six demand projections, as well as 1000 stochastic rainfall replicates. They found that the impact of the different sources of uncertainty on the optimal solutions varied over the 40-year planning period, with some having a greater effect in the short-term and others a greater effect in the long-term. Roshani and Filion (2014) investigated the impact that different climate change abatement strategies have on water main rehabilitation. They consider six carbon abatement strategies with different combinations of two discount rates (1.4 and 8%) and three carbon tax scenarios (no tax, 'fast and deep', and 'slow and shallow'). Using a low discount rate and implementing a carbon tax encouraged the optimization algorithm to find solutions that invested in rehabilitation early, to reduce the cost of continuing leaks, pipe repair, energy use and GHG emissions.

Case studies

The utility of the framework described in the previous sections will now be explored by two different case studies that have different water sources and many variables that need to be considered. These case studies are provided as an example of how the framework could be applied to optimize system operations. The first case study is a managed aquifer recharge (MAR) system that harvests stormwater from an urban creek for irrigation of reserves and sporting fields. This case study demonstrates the importance of analyzing the system by simulation prior to optimization in order to formulate the optimization problem. The second case study is a water supply system in a rural town that supplies potable water from multiple alternative water sources. This system is optimized for minimization of energy use of the many pumps used to transfer water from the various sources.

Ridge Park managed aquifer recharge – case study 1

Ridge Park is located in the Adelaide metropolitan area in South Australia, within the City of Unley local government area. The scheme supplies harvested stormwater to sports fields and recreational reserves in the local area for non-potable irrigation use. The scheme is designed to harvest up to 60 ML of stormwater per year, which occurs over the winter, while in summer the harvested water is used for irrigation. During winter, stormwater from Glen Osmond Creek, an urban waterway, is collected in the Harvest Pond created by a dam on the creek (Fig. 2). Water is then pumped to the Bioretention

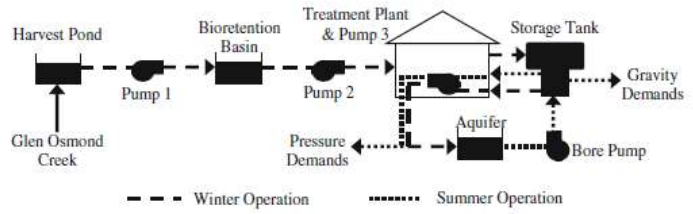

Fig. 2 Ridge Park managed aquifer recharge system process schematic

Basin which provides some treatment, and then pumped to a small treatment plant that includes UV and filtration. Once the water has been adequately treated, it is stored in an above ground tank next to the treatment plant and final pump station. From the Storage Tank, water is injected into an artesian, fractured rock aquifer for long term storage. In summer, when no water is being harvested, water is extracted from the Aquifer and to the Storage Tank, before being pumped or gravity-fed to irrigation points. The Ridge Park Reserve is irrigated by a pressurized irrigation line, as it is at higher elevation than the Storage Tank. Fraser Reserve is also connected to the pressurized system to ensure adequate pressures for irrigation. In total, the pressurized system supplies almost 15 ML of water per year. The remaining seven reserves are on a gravity-fed line which supplies a total demand of roughly 35 ML per year. The layout and details of the system are given in Fig. 3. For more detailed data on this case study, please see the Additional files 1, 2, 3 and 4.

For existing systems, simulation analysis of the current operation is an important first step in formulating the optimization problem. Results of current operational simulations can highlight areas for improvement that can then be focused on in the optimization. The operation of the Ridge Park stormwater harvesting system was split between winter and summer operations and both were simulated in EPANET to determine current pump operational costs. Trigger levels (related to volumes in the three storages as shown in Table 2) control when the pumps in the Winter Harvesting and Injection system turn on and off (Table 2). The Bore Pump is also

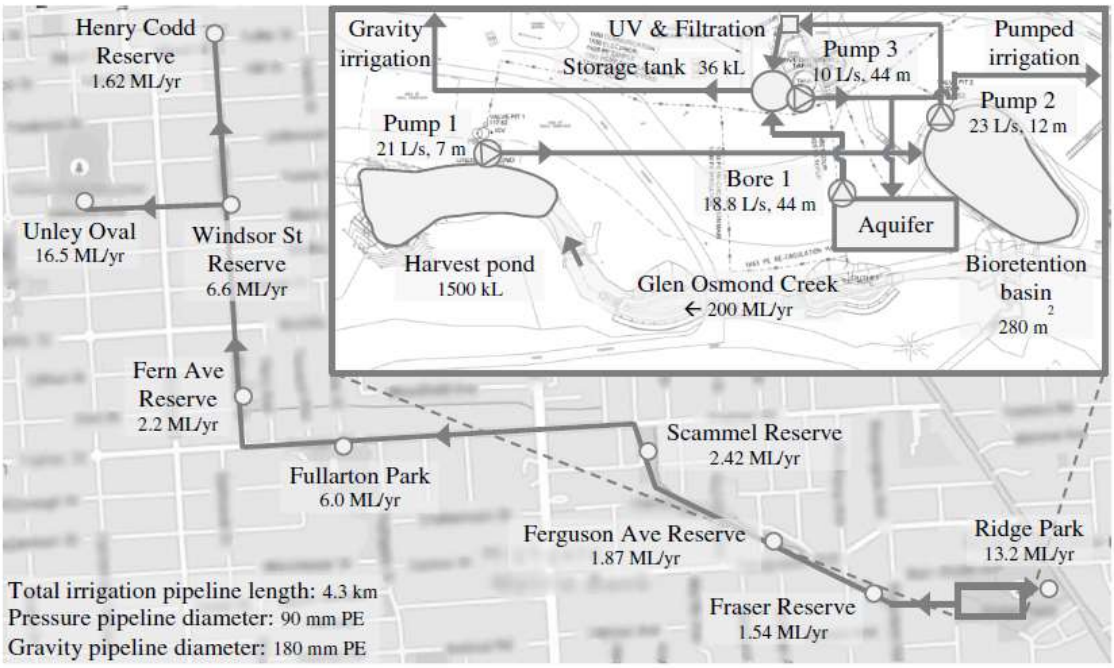

Fig. 3 Ridge Park managed aquifer recharge system layout and data

Table 2 Trigger levels for the Ridge Park system

Storage and trigger level type	Current setpoint		Start pump	Stop pump
	Volume (%)	Level (m)		
Harvest Pond High Level	80	1.6	1	-
Harvest Pond Low Level	50	1.0	-	1
Biofiltration Basin High Level	90	0.80	2	1
Biofiltration Basin Low Level	50	0.59	-	2
Storage Tank High Level	90	2.25	3	2, Bore
Storage Tank Low Level	70	1.75	Bore	3

controlled by trigger levels in the Storage Tank. During summer, Pump 3 is controlled by the irrigation demands, which are on a schedule so that different reserves are irrigated on different nights (Table 3). Pump 3 is a VSP and is operated at 80% of full speed for injection (such that the flow is less than the 7 L/s maximum for injection) and 75% of full speed for irrigation (such that the target pressure downstream of the pump is achieved at the expected demand rates). Both systems were simulated for a period of 1 week in EPANET, with a 15 min hydraulic time step and 5 min reporting time step. Several week-long streamflow series for the available flow in Glen Osmond Creek at a daily resolution were used in the harvesting and injection model (Fig. 4). A peak/off-peak electricity price tariff applied to the entire system; a peak price of 25.53 c/kWh was applied from 7 am to 9 pm on weekdays, and an off-peak price of 15.26 c/kWh was applied over night and on weekends (tariff pattern and simulations started on a Sunday).

Winter harvesting and injection system current pumping operation results

When there was adequate water available, such as in Streamflow Series 1, 4 and 5, the volume of water injected into the aquifer (by Pump 3) was a little over 3 ML per week (Table 4). This was significantly less than the volume available, which reflects the limited flow rate of Pump 3 (7 L/s for injection to the aquifer), as well as the water that would be lost to overflow when the inflow rate is greater than the flow rate of Pump 1 (approximately 22 L/s). The total pump energy cost estimate for the harvesting and injection system ranged from $163 to $267 per week, with an average of $235 per week. Pump 1 was the most cost-effective to run, while Pump 3 was the most expensive. Pumps 1 and 2 operated at similar times throughout the day, however, Pump 2 has much lower efficiencies, which increased its energy use. Pump 3 operated at a lower flow rate but much higher head than Pumps 1 and 2, and was more likely to be switched on for the entire day, which contributed to its higher cost of operation. Pumps 1 and 2 turned on and off very frequently, and operated at a much higher flow rate than Pump 3 (Fig. 5). The flow rate of Pump 3 in Fig. 5(c) reduced over the week as the headloss through the bore increased from assumed clogging of the bore. As the storages are relatively small, in particular the storage tank, it did not take long for them to be filled and emptied (Fig. 6), which contributed to the frequent pump switches. The current trigger levels in the Storage Tank are very close together (70 and 90% volume) as a result of possible pump priming issues that occurred during the commissioning of the system. These close together trigger levels also contributed to the short fill and empty times.

Summer extraction and injection system current pumping operation results

Simulation of the irrigation system gave a total weekly pump energy cost of $90 (Table 5). The Bore Pump was more expensive overall, however, cost less per megaliter than Pump 3. This occurred because while the Bore Pump has a greater efficiency than Pump 3, it also has a higher flow and head, which increased the energy consumption. The higher volume pumped from the bore contributed to a lower cost rate than Pump 3. All of the pumping for this system occurred overnight (Fig. 7)

Table 3 Irrigation demand schedule for the Ridge Park system

Reserve	Demand rate (L/s)	Duration/day (hr)	Start time	Irrigation days
Ridge Park 1	3.53	8.33	9:30 PM	Mon & Wed
Ridge Park 2	3.53	8.67	9:30 PM	Tues & Thurs
Fraser Reserve	1.41	5.83	9:30 PM	Mon & Wed
Ferguson Ave Reserve	2.00	5.00	9:30 PM	Tues & Thurs
Scammell Reserve	2.15	6.00	10:00 PM	Tues & Thurs
Fullarton Park 1	3.85	1.67	10:00 PM	Mon & Wed
Fullarton Park 2	3.85	6.67	10:00 PM	Tues & Thurs
Fern Ave Reserve	3.53	3.33	10:00 PM	Mon & Wed
Windsor St Reserve	2.20	8.00	8:30 PM	Tues & Thurs
Henry Codd Reserve	1.10	8.00	10:00 PM	Mon & Wed
Unley Oval	5.57	9.00	9:00 PM	Sun, Mon & Wed

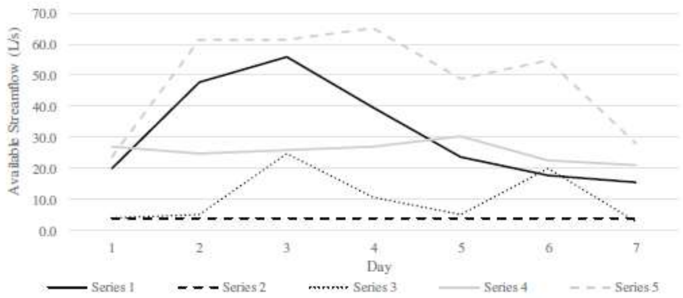

Fig. 4 Streamflow Series used for simulation of the winter harvesting and injection operation

when irrigation of all fields is allowed. The Bore Pump turned on and off very frequently when it was operating, again due to the small capacity of the Storage Tank which meant it did not take long for the pump to fill the operating volume (Fig. 8).

Optimization formulation

Initially, optimization of the Ridge Park system was considered to be an operational problem, however, results of the current operation simulation suggest that design decision variables need to be considered as well. Replacing Pumps 1 and 2 with models that would operate at much lower flow rates (to reduce the headlosses) and increasing the size of the Storage Tank will be considered along with operational decision variables (Table 6). These design decisions would aim to counter-act mismatched pump rates (Pumps 1 and 2 operating at a much higher rate than Pump 3) and small storage volumes that lead to frequent pump switches. Short-term operational decisions include trigger levels in the Harvest Pond, Bioretention Basin and Storage Tank that will govern when pumps are turned on and off, a schedule for irrigation (that is, which reserves will be irrigated at which times), and VSP multipliers for Pump 3. In the current operation, VSP multipliers for Pump 3 were selected to ensure the required flow rate (for injection) and pressure (for irrigation) were achieved. With different levels in the Storage Tank considered, the VSP multipliers for Pump 3 can be altered, especially if efficiency is improved. If the pump priming issues discussed earlier were to be resolved, trigger levels that utilize the full height of the Storage Tank (rather than the 20% range in water elevation that is currently used) would be considered in the optimization. There are also long-term decision variables deciding when to switch between summer and winter operation and vice versa (Table 6). As the scheme injects to and extracts from the aquifer through the same bore, it is not possible to frequently switch between injecting and extracting water, therefore there will be only two switch times per year; one going into winter operation and one going into summer operation. The decision variables presented in Table 6 may all be considered together in an optimization problem, however, they could also be analyzed prior to optimization in a simulation sensitivity analysis. Simulating the system initially with the different pump models and storage tank sizes could help to decide if these actions are worthwhile considering in an optimization formulation. Engineering judgement may be sufficient to determine which pump model(s) would be best to replace Pumps 1 and 2, and therefore reduce the size of the optimization problem.

Constraints on the system include an environmental flow for Glen Osmond Creek, an extraction limit from the Aquifer and meeting the weekly irrigation volumes for each reserve in the summer (Table 7). If there was not enough water harvested over the winter to supply the summer demands, a potable back-up supply is available at a cost. The main objective for this case study is to minimize the pump energy cost; there is also a secondary objective of minimizing the number of pump switches. To create an incentive for the optimization to find solutions that harvest more water, the cost objective includes the energy cost for the harvesting and distribution operation as well as the cost of purchasing potable water if the harvested volume is not enough to supply demand. The objective function is formulated as the cost per volume of water harvested as another means to ensure

Table 4 Current operation results for the winter harvest and injection system

Streamflow Series	Available volume (ML/wk)	Cost (c/kL)			Volume injected (ML/wk)	Total cost ($/wk)
		Pump 1	Pump 2	Pump 3		
1	19.0	0.64	2.28	5.49	3.14	267
2	2.29	0.68	2.32	6.19	1.76	163
3	6.19	0.69	2.23	5.87	2.44	222
4	15.4	0.64	2.24	5.46	3.18	258
5	29.7	0.63	2.25	5.47	3.16	264
Average	14.5	0.66	2.26	5.70	2.74	235

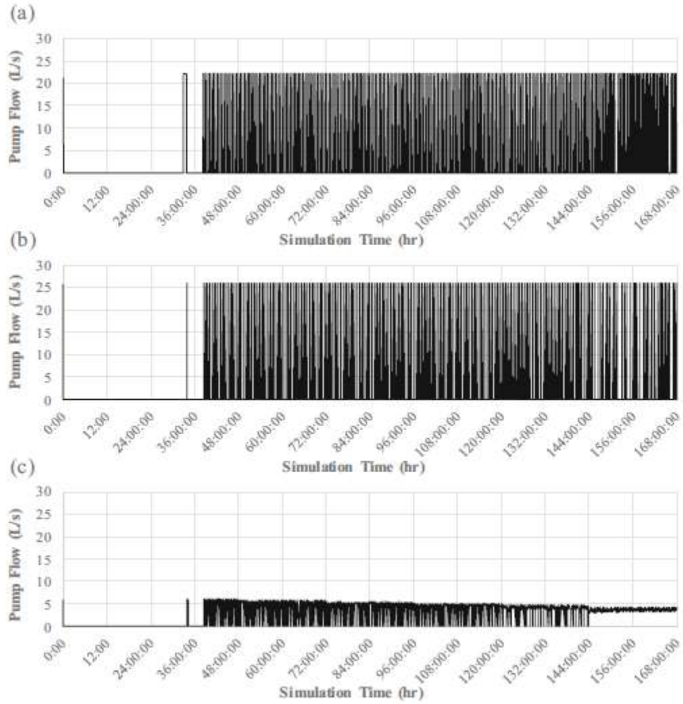

Fig. 5 Pump flows for Streamflow Series 2 for **a** Pump 1, **b** Pump 2 and **c** Pump 3 for a one week EPANET simulation

enough water is harvested from the system during winter to supply summer irrigation. During the conceptualization and design of this scheme, regulations from the South Australian Environmental Protection Authority (EPA), the Department for Environment, Water and Natural Resources (DEWNR) and the Department of Health (DoH) were considered. A license to recharge water into the aquifer was required from the EPA, while the DEWNR regulates how much water can be extracted from MAR schemes. DoH regulations informed the level of treatment implemented and the irrigation practices, which must limit the risk of public exposure.

Orange integrated supply system – case study 2

Orange is a rural town roughly 250 km west of Sydney in the state of New South Wales, Australia. The water supply system serves a population of around 36,800 people with an average annual demand of approximately 5,400 ML. The majority of water supply is from the local surface water catchment, which culminates in the roughly 19,000 ML Suma Park reservoir (Fig. 9). Australia experienced severe drought between 2000 and 2010, and Orange was one of the hardest hit areas in New South Wales. Even with severe water restrictions almost halving the town's demand, Orange had less

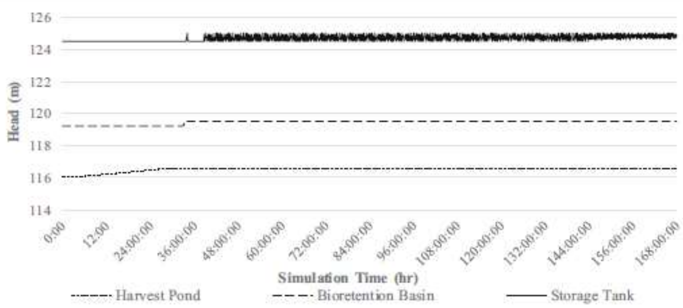

Fig. 6 Storage levels for Streamflow Series 2

Table 5 Current operation results for the summer extraction and irrigation system

Pump	Volume (ML/wk)	Cost (c/kL)
Bore Pump	1.93	3.52
Pump 3	0.57	3.97
Total		$90.3/week

than two years of water supply heading into summer of 2009 and was relying only on surface water catchments (Montgomery Watson Harza, 2011). This prompted the Orange City Council to diversify their water supply, and they therefore developed two stormwater harvesting schemes and a long pipeline from an adjacent catchment, as well as re-opening several groundwater bores. Figure 2 shows a schematic process diagram of the system, which is described below, and Fig. 3 shows the layout (note that the 'Shearing Shed' Bore and 'Bore 5' in Fig. 2 are grouped as the 'Clifton Grove' Bores in Fig. 10). For more detailed data on this case study, please see the Additional files 1, 2, 3 and 4.

Water from the Ploughman's Creek Stormwater Scheme is treated through a series of wetlands, and then combined with water from the Blackman's Swamp Creek Stormwater Scheme. After treatment, this water can be used to top up Suma Park reservoir. Due to the severely low water supply levels during the drought, Emergency Authorization was initially given, and Council subsequently sought approval for use of the stormwater schemes on a permanent basis. Continuous water quality monitoring is undertaken to meet regulations of the Office for Water, the New South Wales Environmental Protection Authority and the Ministry of Health. To the authors' knowledge, this is the only system in Australia that has been approved to use harvested stormwater for potable supply. In order to use harvested stormwater for potable supply, the Council had to meet requirements of the Office for Water. The Macquarie pipeline transfers water from the adjacent Macquarie River catchment to Suma Park reservoir. It is 38 km long and requires more than 600 m of pumping head. Each of the three pumping stations has two pumps operating in parallel. Water from the groundwater bores is pumped first to balancing storages and then to Suma Park reservoir, with a combined licensed volume of 462 ML per year. Water from all of the sources is combined in Suma Park reservoir and treated at a water treatment plant before being delivered to consumers.

The Orange City Council is interested in optimizing the operation of this while delivering a secure yield from Suma Park Dam. In addition to the primary objective of minimizing energy cost, there are objectives of minimization of spill from Suma Park reservoir, minimization of (perceived) environmental impact, maximization of (perceived) water quality, and minimization of energy use. The Council has an explicit objective to minimize spill to ensure water and energy are not wasted by pumping from one of the three alternative sources to fill up Suma Park reservoir just before a rainfall event that would supply water from the natural catchment at no cost or energy output. As this system supplies potable demands, it is undesirable to apply water restrictions to consumers, thus minimizing time spent in restrictions is important. Objectives for the perceived environmental impact and water quality will be formulated as a preference ranking between the different sources based on community views of which sources are better for the environment and water quality. The constraints of the problem include environmental flows for the Macquarie River (downstream of the pumping station offtake point) and stormwater schemes, a water source license for the Macquarie River and extraction limits on the groundwater bores (Table 8).

Energy optimization formulation

In this section, the developed framework is applied to the Orange case study to help set up the optimization procedure and identify the components and data to be modeled. Note that the model has been built taking into account all possible objectives of the system, however, the example of results presented here will focus on the minimization of energy consumption.

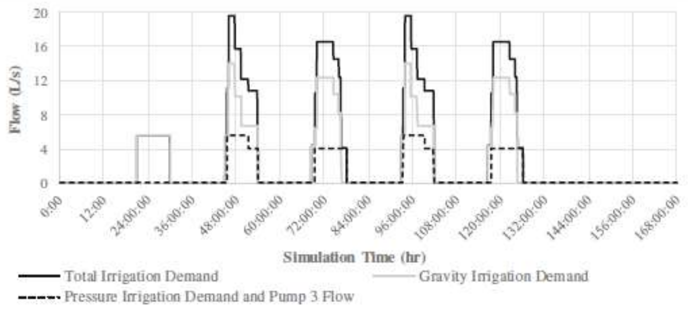

Fig. 7 Current demand rate and pump flows for the irrigation system

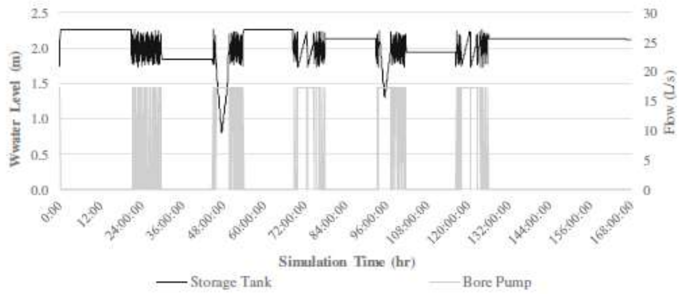

Fig. 8 Storage tank level and bore pump flow for the summer extraction and irrigation system

As all components of the system have already been constructed and considered sufficient for the operation of the system, there are no design decisions to consider, only operating decisions. For this case study, operating decisions consist of trigger levels in the various storages. These types of decision variables are chosen considering the control system available at each pump station (based on storage levels and not on time of the day) and the fact that the controls have to be defined for an operational horizon of 1 year or longer. As all of the pump stations have two or more pumps arranged in parallel, having different trigger level values may have a large impact on the operating point of the pumps and consequently their energy consumption. It is also likely that different trigger levels will be chosen for peak and off-peak electricity tariff periods when they are included in a cost optimization. For this system a peak/off-peak electricity tariff applies on weekdays, with weekends priced at the off-peak rate. A peak monthly electrical energy demand charge also applies to the Macquarie River pipeline pumping system. In order to assess the performance of different tank trigger levels, the infrastructure to be modeled includes the natural and urban catchments for the surface water and stormwater systems respectively, Suma Park reservoir, pipelines and pumps in the groundwater, Macquarie River and stormwater systems, and wetlands and storage ponds in the stormwater systems.

In general, the system could be modelled using hydrologic models, mass balance models, and/or hydraulic models. The choice of which model(s) will be used depends on the objectives and the processes to be modelled, on the available data and the computational times. In particular, hydrologic modeling is usually used to transform rainfall to runoff for the natural and urban catchments. For this case study, inflows inputs or approximate relationships between rain and flows were provided by previous studies by the Orange City Council. Hydraulic models are usually used for short term operations: pump energy costs can be computed accurately based on the hydraulic equations. Mass balance modeling is usually used for assessing the system in long term operations, as it can

Table 6 Possible decision variables for the Ridge Park MAR scheme

Short-term winter harvesting and injection operation	
Pump 1 Off	Harvest Pond Level Low
	Bioretention Basin Level High
Pump 1 On	Harvest Pond Level High
Pump 2 Off	Bioretention Basin Level Low
	Storage Tank Level High
Pump 2 On	Bioretention Basin Level High
Pump 3 Off	Storage Tank Level Low
Pump 3 On	Storage Tank Level High
Pump 3 Speed	Storage Tank Level
Short-term summer extraction and irrigation operation	
Bore Pump Off	Storage Tank Level High
Bore Pump On	Storage Tank Level Low
Irrigation Schedule	Days of Irrigation at each Reserve
	Start Time of Irrigation at each Reserve
Pump 3 Speed	Required Demand Rate
Long-term operations	
Day to Switch Between	Summer to Winter
Seasonal Operational Regimes	Winter to Summer
System Design	
Storage Tank Size	Doubled, 5 times, 10 times current size
Pumps 1 and 2	Selection of pump curves with lower operating rates

Table 7 Possible constraints for the Ridge Park MAR scheme

Constraint	Value
Glen Osmond Creek Environmental Flow	>2 L/s
Aquifer Extraction in Summer	<80% of Injection Volume
Pressurized System Demands	>15 ML/year
Gravity System Demands	>37 ML/year

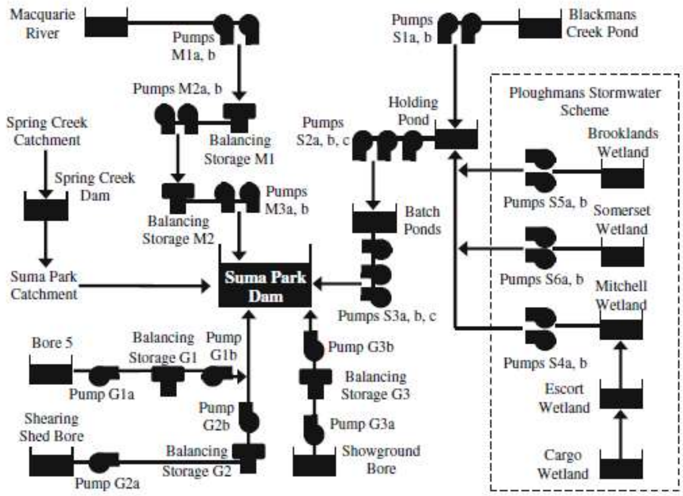

Fig. 9 Orange integrated supply system process schematic – inflow to Suma Park Dam

quickly compute the water available after evaporation and other losses in the system have occurred and after minimum environmental flows have been released. It cannot, however, take into account the non-linearity in the hydraulic equations and therefore assumptions need to be made in regard to the flow delivered by the pumps in the system. While hydraulic simulation would be most appropriate for the pumping stations in the system as they have multiple pumps and sometimes have connected pipelines, mass balance models would need to be used to compute the additional processes, such as evaporation and the release of minimum environmental flows that need to be taken into account given the long duration of the simulation. During an optimization process, simulating each potential solution using both a mass balance and a hydraulic model would increase considerably the computational time, particularly if data transfer between the two models was required. It is therefore suggested that the primary simulation tool should be a hydraulic solver. Rainfall-runoff modeling could be performed pre-optimization, and supplemental code added to a hydraulic model to account for functionality of a mass balance model. This would allow for consideration of the evaporation from and rainfall directly to reservoirs, changes to demands based on water restrictions and environmental flows that depend on the combined volume of two reservoirs (Spring

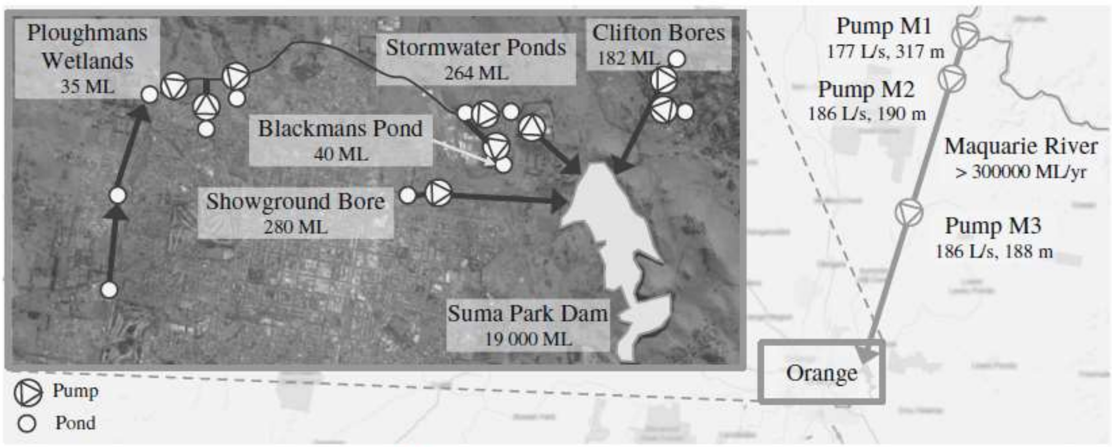

Fig. 10 Orange integrated supply system layout and data

Table 8 Constraints for the Orange integrated supply system

Constraint	Value
Macquarie River Environmental Flow	>108 ML/day
Blackmans' Creek Environmental Flow	>20 ML/day
Ploughmans' Creek Environmental Flow from Pump S4	>0.4 ML/day
Ploughmans' Creek Environmental Flow from Pump S5	>2 ML/day
Ploughmans' Creek Environmental Flow from Pump S6	>2 ML/day
Clifton Grove (Shearing Shed and Bore 5) Aquifer Extraction	<182 ML/year
Showground Aquifer Extraction	<280 ML/year
Macquarie River Extraction License	<12 ML/day

Creek and Suma Park), infiltration losses when transferring water between reservoirs and peak power demand charges.

Another important issue to consider is what simulation time step should be used. Using a shorter time step will increase the accuracy of this hydraulic analysis and often results in feasible optimization times for storages that empty or fill in a day or two (as would likely be the case for the stormwater ponds and Macquarie pipeline balancing storages). Simulating the behavior of Suma Park dam is more challenging, however, as the variations in the water levels can have a period of several years. Thus, the computation times with a short time step become prohibitively long. A balance needs to be found between using a short enough time step for the detailed hydraulics and a long simulation time for the large storages without having a prohibitively large computational time. Given the data availability (there is 118 years of rainfall and inflow data available, with a daily time step) the time step chosen is 1 day.

Given that the time-step is automatically shortened by the hydraulic solver chosen (EPANET in this case), the model of the real system has been simplified in order to avoid excessive computational times. In particular, given that the levels in the balancing storages along the Macquarie pipeline vary rapidly, these storages were removed and the pipeline simulated with two parallel pumps, each representing the equivalent of the three stages of pumping (that is, the pump curves for Pumps M1a and b in Fig. 2 were adjusted such that they represented Pumps M2a, M3a and Pumps M2b, M3b as well). This simplification is considered acceptable as the pumps in series in the Macquarie pipeline will usually be operated at the same time, given that each pump will still be controlled also by the level of Suma Park Dam. Longer computational times were also caused by the small storages after the groundwater bores. The pumps used for extraction from the aquifers (Pumps G1a, G2a and G3a in Fig. 2) operate at relatively consistent rates, and as such they could be removed from the model and their energy use accounted for relative to the volume pumped from the second pump in each system (Pumps G1b, G2b and G3b respectively). To take into account the limited volume available from the groundwater bores, the storage tanks in the groundwater system each had a volume equivalent to a year's allocation for the respective bores. All of the stormwater pumps except for Pump S2c and Pump S3c, which are standby pumps and not in use, were included in the model. As well as the operating point of the pumps changing depending on the number of pumps used in parallel, there may be slight differences in efficiency and therefore energy use, and thus including all pumps here provided more accuracy.

All of the pumps included in the model were controlled using rule-based controls in EPANET, with conditions based on levels in one or more storages as well as time. Conditions based on downstream storages were considered as decision variables, while conditions based on upstream storages were fixed (Table 9). For the Macquarie pumps, there were also conditions based on the flow in the river to ensure that no water would be taken when there was not enough water available. There were four possible decision variables for each pump, a lower and upper trigger level in both the peak and off-peak time. For optimization of energy use, only two are required, as peak and off-peak tariffs are not considered. As the model was set up for other objectives including cost, which does use a peak and off-peak electricity tariff, the capability to choose different trigger levels in different periods was incorporated. A maximum of 15 pump switches per day per pump were allowed, and the end level of Suma Park Dam was constrained to 16 m (to be approximately the same as the start level). Based on license conditions, Macquarie River water can only be used when the Suma Park Dam level is below 90%, so choices for Pump M1a and M1b trigger levels in Suma Park Dam are more restricted than for other pumps.

Energy optimization results

Minimization of pump energy use over the longer term is presented here as an example of optimization of this system. Note that the system is simulated over 1 year, at a daily time step in EPANET. Additional computer code was added to the EPANET hydraulic simulation to take into account other process such as rainfall to and evaporation from storages. This code essentially adds a mass balance component to the hydraulic simulation. Historical rainfall for the catchments in the system was modelled in MUSIC hydrologic software to develop inflow series for the ponds and reservoirs. For this optimization the year with the closest to average rainfall was used, however, other years of rainfall were available and this optimization could be extended to consider other climate conditions.

Table 9 Decision variables and fixed controls for the Orange integrated supply system

Pump station action	Storage(s) controlling operation	Decision variable or fixed
Macquarie Pump M1a, M1b Off	Suma Park Dam Level High	Decision Variable
Macquarie Pump M1a, M1b On	Suma Park Dam Level Low	Decision Variable
Stormwater Pump S1a, S1b Off	Holding Pond Level High Blackmans Stormwater Pond Level Low	Decision Variable Fixed
Stormwater Pump S1a, S1b On	Holding Pond Level Low Blackmans Stormwater Pond Level High	Decision Variable Fixed
Stormwater Pump S2a, S2b Off	Batch Ponds Level High Holding Pond Level Low	Decision Variable Fixed
Stormwater Pump S2a, S2b On	Batch Ponds Level Low Holding Pond Level High	Decision Variable Fixed
Stormwater Pump S3a, S3b Off	Suma Park Dam Level High Batch Ponds Level Low	Decision Variable Fixed
Stormwater Pump S3a, S3b On	Suma Park Dam Level Low Batch Ponds Level High	Decision Variable Fixed
Stormwater Pump S4a, S4b Off	Holding Pond Level High Mitchell Wetland Level Low	Decision Variable Fixed
Stormwater Pump S4a, S4b On	Holding Pond Level Low Mitchell Wetland Level High	Decision Variable Fixed
Stormwater Pump S5a, S5b Off	Holding Pond Level High Brooklands Wetland Level Low	Decision Variable Fixed
Stormwater Pump S5a, S5b On	Holding Pond Level Low Brooklands Wetland Level High	Decision Variable Fixed
Stormwater Pump S6a, S6b Off	Holding Pond Level High Somerset Wetland Level Low	Decision Variable Fixed
Stormwater Pump S6a, S6b On	Holding Pond Level Low Somerset Wetland Level High	Decision Variable Fixed
Groundwater Pump G1 Off	Suma Park Dam Level High	Decision Variable
Groundwater Pump G1 On	Suma Park Dam Level Low	Decision Variable
Groundwater Pump G2 Off	Suma Park Dam Level High	Decision Variable
Groundwater Pump G2 On	Suma Park Dam Level Low	Decision Variable
Groundwater Pump G3 Off	Suma Park Dam Level High	Decision Variable
Groundwater Pump G3 On	Suma Park Dam Level Low	Decision Variable

NSGAII (Non-dominated Sorting Genetic Algorithm II) software was used for the optimization, with five random seeds, a population size of 50, 100 generations and probabilities of crossover and mutation of 0.8 and 0.02 respectively. In the best solution found, the system used a total of 793 MWh of energy over the entire year. Table 10 shows the volume of water pumped from each source to Suma Park Dam (and supplied from the local catchment) and the energy used by each of the pumps for the optimal solution. Pumping from the Macquarie is very energy intensive so this is only used at the very end of the simulation when the level in Suma Park Dam is very low, in order to achieve the end target level constraint (Figs. 11 and 12). Groundwater and stormwater sources are used initially to increase the level of Suma Park Dam to its maximum, and then not used again until around Day 160 when the level in the dam has dropped again. Only one of the Macquarie pumps is used, as, despite operating at a lower energy efficiency point, it uses less energy overall than operating two pumps in parallel. In dryer years, both pumps may need to be utilized in order to ensure supply to Suma Park Dam. Nearly all of the available groundwater license is used; G1 and G2 have a combined license of 180 ML/year, and G3 280 ML/year. Groundwater is more energy intensive than stormwater, however, it can be used at any time throughout the year, while stormwater is reliant of inflow. Most of the stormwater provided to Suma Park Dam came from the Blackman's Creek scheme (S1) rather than the Ploughman's Creek scheme (S4, S5 and S6). While the storage capacity of the Blackman's Creek scheme is much lower, the pump capacity and energy efficiency is much greater than in the Ploughman's Creek scheme, so it provides more water.

Table 10 Volume of water pumped/supplied and energy used in the optimal energy solution

Source	Pump	Volume (ML)	Energy (MWh)	Energy Rate (MWh/ML)
Macquarie River	M1a	0	0	0
	M1b	74	150	2.02
	Total	74	150	2.02
Groundwater[a]	G1	24	11	0.46
	G2	146	79	0.54
	G3	235	106	0.45
	Total	405	196	0.48
Stormwater	S1a	258	39	0.15
	S1b	479	71	0.15
	S2a	828	65	0.08
	S2b	237	21	0.09
	S3a	1022	170	0.17
	S3b	22	5.5	0.25
	S4a	178	41	0.23
	S4b	12	3.1	0.27
	S5a	24	4.8	0.20
	S5b	56	11	0.19
	S6a	60	11	0.18
	S6b	26	5.0	0.19
	Total[b]	1044	447	0.43
Spring Creek and Suma Park Catchment	-	3865[c]	-	-

[a]The energy consumption for the groundwater pumps includes both the transfer and bore pumps, i.e. the energy for Pump G1 includes G1a (not modelling in EPANET, energy use estimated from volume) and G1b (modelled in EPANET)
[b]The total volume supplied by the stormwater schemes is measured as the combined volume supplied by Pumps S3a and S3b (which discharge to Suma Park Dam), while the total energy is the total of all pumps
[c]This is the volume supplied by the natural catchment for the town's consumption, the total inflow from the catchment is greater than this however some is used to provide environmental flows and some spills

Conclusions

A generalized framework for the optimization of the design and operation of water supply and distribution systems has been developed and two case study systems have been used as examples of how to apply it. The framework is comprised of several components; the options component describes the design and operational decision variables for the optimization, the infrastructure component covers the infrastructure aspects of the system that need to be modeled and their data requirements, the analysis component includes the simulation of the system and evaluation against the objectives and constraints, and finally the government policy component describes the regulations that may affect other aspects of the framework. These components fit within an optimization algorithm structure, which firstly generates potential solutions using the decision variables in the options component, models the system according to the infrastructure component and evaluates potential solutions using the analysis component. The evaluation of potential solutions then feeds into the solution space which informs how the decision variables are changed in the next set of potential solutions. Sensitivity analysis of parameters will significant uncertainty should be undertaken to ensure robust solutions. The framework also applies to simulation of systems prior to or without optimization.

The Ridge Park MAR Scheme Case Study harvests stormwater from an urban creek and stores it in an aquifer, to be extracted at a later time and used as non-potable supply for irrigation of sporting fields and reserves. For this case study, and similar ones, the simulation of the system may be simplified by splitting the system into two parts, one for the components of the system used in winter operation (harvesting and injection) and one for the components used in summer operation (extraction and irrigation). This system highlighted the importance of simulation and analysis prior to optimization, in order to focus the formulation of the optimization problem. The Orange Integrated Supply

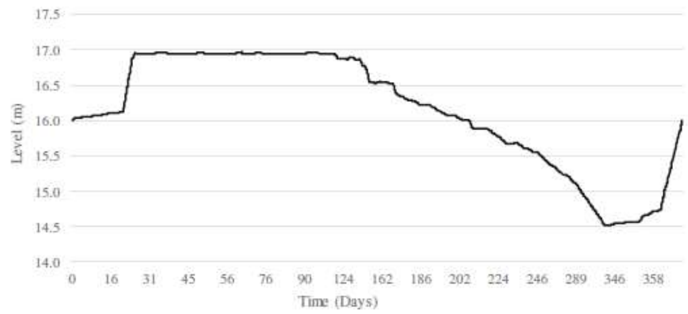

Fig. 11 Variation in Suma Park Dam level for the energy optimal solution

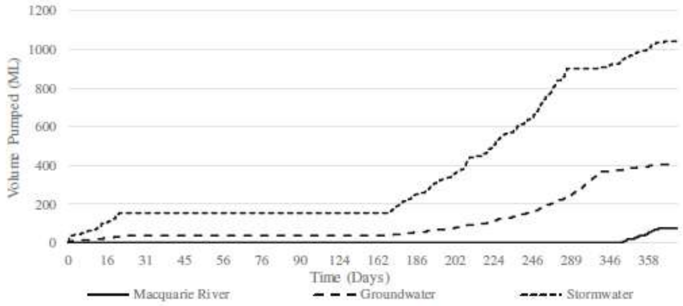

Fig. 12 Volume pumped from each source to Suma Park Dam for the energy optimal solution

System Case Study uses multiple water sources; natural catchment water, harvested stormwater, imported water and groundwater to supply potable demands. For this case study, finding an appropriate combination of simulation models and time step and simulation duration is important in order to provide accuracy in representing both long- and short-term operations without excessive computational times. Optimization of pump energy use for this system indicated that the groundwater and stormwater supplies are more desirable to supplement natural inflows than the imported water from the Macquarie River, which required a lot of energy to transfer water over a long distance and against a high elevation head.

The framework is generalized, and so could be applied to other water supply and distribution systems, particularly those using non-traditional water sources, to optimize their design and operation. While the framework attempts to cover all aspects of water supply in a generalized manner, it does have some limitations. Along with the supply of water, there will always be a need to manage wastewater. Apart from considering recycled wastewater as a source, this framework does not cover wastewater systems in terms of collection, transport, treatment and potential discharge of wastewater into the environment. Treatment of raw water supplies is included in the framework, however, the details of such treatment and measurement of water quality throughout a water distribution system are not focused on as much as the design and operation of the systems. A difficulty of applying this framework will be the definition of the boundary of a system and which aspects should be analyzed. Currently, there does not exist commercial software that has all of the capabilities considered in the framework (i.e. both hydrologic and hydraulic simulation). This means that specialist simulation models may need to be developed for particular systems (as was done for the second case study). Future developments in simulation software may reduce the difficultly of combining hydrologic, mass balance and hydraulic considerations and remove the need for specialist tools built for individual systems. In the future, the framework should be tested with other case study systems to fully investigate its benefits.

Additional files

Additional file 1: CS1 Ridge Park Data Summary. (PDF 548 kb)
Additional file 2: CS1 Ridge Park Hydrological Data. (XLSX 3786 kb)
Additional file 3: CS2 Orange Data Summary. (PDF 537 kb)
Additional file 4: CS2 Orange Hydrological Data. (XLSX 13245 kb)

Abbreviations

AMALGAM: A Multi-ALgorithm Genetically Adaptive Multi-objective method; DEWNR: Department of Environment, Water and Natural Resources (South Australia); DoH: Department of Health (South Australia); EPA: Environmental Protection Agency (Australia); EPANET: Environmental Protection Agency NET hydraulic simulation software; GCM: Global circulation model; GHG: Green house gas; IPCC: Intergovernmental panel on climate change; MAR: Managed aquifer recharge; MUSIC: Model for urban stormwater improvement conceptualization; NSGAII: Non-dominated Sorting Genetic Algorithm II; SRES: Special report emissions scenarios; VSP: Variable speed pump; WDS: Water distribution system; WEAP: Water evaluation and planning system

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Availability of data and materials

The datasets supporting the conclusions of this article are included within the article and its additional files. This data has been collated by Lisa J. Blinco, the corresponding author of this paper. The following additional files are available:

- CS1 Ridge Park Data Summary.pdf
- CS1 Ridge Park Hydrological Data.xlsx
- CS2 Orange Data Summary.pdf
- CS2 Orange Hydrological Data.xlsx

Competing interests

The authors declare that they have no competing interests.

Authors' contributions
LJB was responsible for the development of the conceptual framework, review of literature and drafting the manuscript. MFL provided feedback and recommendations in the development of the framework and helped to draft the manuscript. ARS provided feedback and recommendations in the development of the framework and helped to draft the manuscript. AM provided feedback and recommendations in the development of the framework and helped to draft the manuscript. All authors read and approved the final manuscript.

Consent for publication
Not applicable.

Ethics approval and consent to participate
Not applicable.

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Appendix C: Final Published Version of WDSA 2014 Conference Paper

Paper presented at the 16th Conference on Water Distribution System Analysis, WDSA 2014 in Bari, Italy.

Genetic Algorithm Optimization of Operational Costs and Greenhouse Gas Emissions for Water Distribution Systems

Blinco, L.J., Simpson A.R., Lambert, M.F., Auricht, C.A., Hurr, N.E., Tiggemann, S.M., and Marchi, A.

School of Civil, Environmental and Mining Engineering

The University of Adelaide, Adelaide, SA 5005 Australia

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16th Conference on Water Distribution System Analysis, WDSA 2014

Genetic Algorithm Optimization of Operational Costs and Greenhouse Gas Emissions for Water Distribution Systems

L.J. Blinco[a,b]*, A.R. Simpson[a,b], M.F. Lambert[a,b], C.A. Auricht[c], N.E. Hurr[a], S.M. Tiggemann[d], A. Marchi[a]

[a]School of Civil, Environmental and Mining Engineering, University of Adelaide, Adelaide 5005, Australia
[b]Cooperative Research Centre for Water Sensitive Cities, PO BOX 8000, Clayton, Victoria, 3800, Australia
[c]South Australian Water Corporation, 250 Victoria Square/Tarntanyangga, Adelaide 5000, Australia
[d]KPMG, 151 Pirie Street, Adelaide 5000, Australia

Abstract

A genetic algorithm (GA) model for water distribution system (WDS) operation has been developed, optimizing pumping by time-based scheduling and tank trigger levels. An important focus was the minimization of operational greenhouse gas (GHG) emissions, in conjunction with operational economic cost, to provide a comprehensive solution to the pumping problem. Various possible future energy scenarios have been investigated to determine the effect of varying GHG emissions factors on the optimal operational decisions for WDSs. The interface developed in this research allows users to apply the optimization algorithm to a variety of water networks with full customization of inputs and parameters.

Peer-review under responsibility of the Organizing Committee of WDSA 2014

Keywords: Genetic algorithm; optimization; pump operation; greenhouse gas emissions; water distribution systems

1. Introduction

The operation of WDSs serves one of society's most basic needs, that being the provision of potable water, however these systems are also significant consumers of energy resources. Energy costs can account for up to 65% of a water utility's operating budget and as such, models that optimize pump operations can lead to large cost savings for water utilities [1]. Worldwide and especially in Australia, the efficient use of both water and energy resources has come under scrutiny. The implications associated with climate change are expected to exacerbate these

* Corresponding author. Tel.: +61 8 8313 5451.
E-mail address: lisa.blinco@adelaide.edu.au

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concerns, and consequently one of the major challenges facing society is the efficient utilization and conservation of existing resources. It has become a priority for the design and operation of WDSs to incorporate minimization of environmental impacts in conjunction with economic optimization [2]. GAs represent an efficient method for the optimization of non-linear problems, particularly when applied to complex WDSs. They apply principles of natural selection to a population of solutions, gradually converging on optimal or near-optimal solutions in a relatively small number of evaluations [3]. When applied to the optimization of WDSs, GAs have been found to perform significantly better than other optimization techniques in areas of final solution optimality and iterative efficiency [4]. In the past, pumping operation optimization has generally minimized costs only, with no consideration for GHG emissions. This was achieved by maximizing pumping during off-peak electricity tariff periods and minimizing the static head [5]. Most pumping system operations use either trigger levels or scheduling. Lower and upper trigger levels represent the tank water levels at which the pump(s) will turn on or off respectively. Pump scheduling involves a set of temporal rules indicating when pumps should be switched on or off during the day, requiring a good estimation of the daily water demand. Kazantzis *et al.* [5] used a GA to find optimal pumping strategies incorporating both trigger levels and scheduling to minimize energy costs in WDSs. To properly account for the GHG emissions of WDSs the sources of electricity should be identified, as each will have different GHG emissions per unit of energy produced [6]. An 'emissions factor' is used to convert energy use to GHG emissions, considering all types of GHGs and their global warming potential as an equivalent mass of carbon dioxide (CO_2-eq). Many previous studies have used an average GHG emissions factor value for the region, including Dandy *et al.* [6] and Wu *et al.* [2,7]. A large amount of electricity is required for pumping, particularly during times of peak water demand, which often correspond to times of peak electricity demand. Scheduling pumps to operate in off-peak periods may provide cost savings through taking advantage of variable tariffs. A future approach, primarily concerned with GHG emissions, may be to pump steadily throughout the day with a VSP, or in response to demands rather than in response to electricity prices. This would reduce energy consumption through the use of smaller velocities leading to a smaller friction head.

This paper describes the development of a GA optimization model to solve the pump operations problem considering trigger levels, scheduling and VSPs. There is a need for a user-friendly, flexible model that can easily be applied to any network and used to develop pump operational strategies that reduce cost, GHG emissions and energy consumption. In order to implement a more comprehensive assessment of GHG emissions than has previously been considered, potential future energy scenarios and specific GHG emissions factors for each energy source are used. The model is linked to hydraulic simulation software EPANET and a Microsoft Excel interface, allowing the user to fully customize the program for any network specification and optimization parameters. Application of the model provides insight into the trade-offs between cost, GHG emissions and energy in WDS pump operation.

2. Methodology

2.1. Environmental objective assessment

In order to more accurately take into account the different energy sources providing electricity for pumping, different emissions factors were used for each type of electricity energy source. Multiple energy source scenarios have been considered, each with different electricity generation technologies contributing to the energy required for pumping (Fig. 1). South Australia's current energy breakdown consists mainly of gas, brown coal and wind [8] (Fig. 1 (a)). Three possible future energy scenarios representing a range of predictions from the Australian Energy Market Operator (AEMO) [9] were selected to be used in this research (Fig. 1 (b), (c) and (d)). Beyond Zero Emissions have produced two reports concerning Australia's energy future; one proposing the replacement of Port Augusta's (in South Australia's north) coal fired power station with concentrated solar thermal technology [10] and the other investigating using 100% renewable energy in Australia [11]. Both of these scenarios have been considered in this paper (Fig. 1 (e) and (f)).

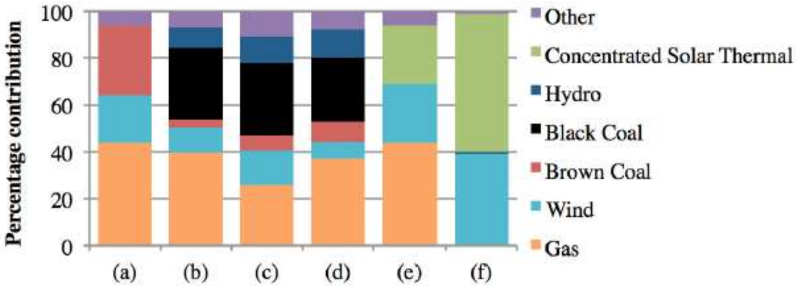

Fig. 1. Energy source scenarios (a) current South Australian (b) AEMO – fast rate of change (c) AEMO – oil shock and adaption (d) AEMO – slow rate of change (e) concentrated solar thermal at Port Augusta and (f) Australia 100% renewable. 'Other' includes oil, geothermal, biomass and solar photovoltaic.

The emissions factors were also adjusted to account for the variation in output from solar photovoltaic systems throughout the day, which has the greatest output during the afternoon. This gave a set of six scenarios, each with unique values and daily variations in emissions factors. Typically, any previous modelling involving the calculation of GHG emissions has not taken into account the daily variation in emissions factors. The ability for users to select and customize the energy scenarios and use hourly emissions factors made the optimization model robust to potential future energy conditions.

2.2. Genetic algorithm formulation

The models developed in this research were adaptations of a GA first developed by Keall [12], which used integer coding to optimize the design of pipe diameters. This research significantly modified the original GA structure to optimize pumping operations, incorporating a choice of objective functions to optimize; including minimization of cost, GHG emissions, energy, and a multi-objective combination of cost and GHG emissions with a user-specified carbon price. The model included options for users to choose types and values of GA operators, such as selection, crossover and mutation, as well as enabling customization of the GA parameters, such as population size, number of generations, and stopping criteria. The value of each objective function was calculated in terms of units per volume of water pumped, to remove any bias between solutions that pump slightly different amounts of water over the day. Raw values of costs, GHG emissions, energy and volumes pumped during peak and off-peak were also output from the model to provide users with comprehensive information about the operational performance. The objective function for cost was given by

$$OC = \frac{ET_p \times E_p + ET_0 \times E_0}{V} \tag{1}$$

where OC = operational cost in \$/m^3, ET = electricity tariff in \$/kWh, E = energy consumption in kWh, V = volume of water pumped over whole day in m^3, subscript P = peak period and subscript O = off-peak period. EPANET was utilized to determine energy consumption for each time period, and subsequently the total energy used for pumping during peak and off-peak periods, as well as the volume pumped. Electricity tariffs could be customized by the user, typical values of 9 c/kWh in the off-peak period, from 11pm to 7am, and 22 c/kWh in the peak period were used in this research. The objective function for GHG emissions was given by

$$OGHG = \frac{\sum_i EM_i \times E_i}{V} \tag{2}$$

where $OGHG$ = operational GHG emissions in kg CO_2-eq/m^3, EM_i = emissions factor in kg CO_2-eq/kWh, E_i = energy (in kWh) at each time step i.

Minimization of energy consumption acted as a surrogate for optimization of cost or GHG emissions where a flat electricity tariff and constant emissions factor were used. The energy usage from each time step was summed to give the total daily energy consumption and divided by the volume pumped to give the objective function value. A multi-objective optimization was also available and this combined the cost and GHG objectives using a user-defined carbon cost. The objective function for this optimization was given by

$$OBJ = OC + CC \times OGHG \tag{3}$$

where OBJ = value of the objective function in \$/m^3 and CC = user-defined carbon cost in \$/kg CO_2-eq. Australia's current carbon price is \$25.40 per ton CO_2-eq, however there is uncertainty regarding future values, and by enabling users to vary this price they are able to customize the importance weighting of GHG emissions.

A number of constraints were incorporated into the GA to ensure that the solutions found were hydraulically feasible; these included minimum and maximum values for nodal pressures, pipe velocities and unit headloss. These constraints could be the same for all nodes or pipes within a network, or customized for each element individually. The user is also able to specify a maximum number of pump switches per day, which may be used to constrain pump maintenance costs. Tank balancing at the end of each time period can also be selected as a constraint, with users able to specify the maximum amount by which the storage tank's ending value should differ from its starting value each day. To account for emergency and dead storage, a minimum tank level could be specified. Each constraint had an associated penalty value that could be modified to reflect the relative importance of that constraint.

2.3. Optimization model development

Pump systems generally operate based on one of two operational control mechanisms; pump scheduling or trigger levels, as described previously. In order to reduce operational costs, the pumping mechanism should minimize the amount of pumping that occurs during the peak electricity tariff period; this is usually achieved when the water level in the tank is at its maximum at the beginning of the peak period and at its lowest allowable level at the end of the peak period. Three distinct optimization models were produced, each incorporating a different pumping regime. These models begin the simulation at the beginning of the off-peak period, with the tank at its minimum allowable level. This serves as a 'known' starting point for an optimal solution and also means that the ending level of the tank is likely to be close to the initial level, as less pumping will benefit any objective function chosen. This is important to mitigate long-term filling or depletion of the tank.

The first optimization model developed used lower and upper trigger levels; the GA had two decision variables, one for each of the trigger levels. This model presents an effective method for keeping the tank level within a specified operating range, however, does have conflicting optimal solution characteristics. Having a high upper trigger level results in increased static head and therefore more energy consumption for the same volume of water pumped. Having a low upper trigger level results in increased pumping during the peak period; the tank cannot become full before the start of this period, and therefore must pump continuously throughout to fulfil the demands on the tank. The second model utilized variable trigger levels to mitigate the above inefficiencies. This model had three decision variables; a lower trigger level, upper trigger level and reduced upper trigger level. The additional reduced upper trigger level could be applied during most of the simulation period to decrease the static head. The ultimate upper trigger level came into effect at a switch time before the end of the off-peak period to allow the tank to fill before the peak period began, such that an optimal solution would have the tank full at the beginning of the peak electricity tariff period. This switch time was a parameter that could be customized by the user. The final model optimized a pump-scheduling regime, in which the decision variables were the pump speed multipliers at each time interval. If VSPs were used, the possible values for the pump speed multipliers could be specified by the user, and would typically range from 0.8-1.0, as well as 0 to represent the pump being off. For fixed speed pumps (FSPs), only multipliers of 0 (off) and 1 (on) were required. This model includes the capability for the user to specify this time interval to reflect different demand patterns and pumping restrictions or requirements. For example using half-hourly time intervals may provide more operational flexibility compared to hourly time intervals, with 48 decision variables compared to 24. The user could specify the possible pump speed multipliers, depending on the capability of the pumps and the WDS characteristics.

2.4. The Excel interface

A user-friendly interface, based on a significant expansion of work by Sankey [13], was developed in Microsoft Excel to enable users to easily set the GA parameters, choice tables and other factors for the model. The interface was written in Visual Basic computer programming language within Excel, with buttons and user forms providing a convenient user interaction with the program, enabling them to setup and customize their optimization with ease. Most of the GA parameters, as well as standard constraints, penalties, electricity tariff parameters and the EPANET input file name are input by the user in the 'Problem Configuration' form. Various screens then allow for choice table input, refinement of constraints and input of GHG parameters. For the top twenty solutions of each simulation, information relating to the values of the decision variables and key results such as cost, GHG emissions, volumes pumped and energy usage are presented. Significant modifications to the original interface include the addition of constraints such as maximum headloss, maximum number of pump switches and tank balancing. Further modifications included the ability to optimize the problem for various objective functions and a screen facilitating the input of GHG and energy parameters. User buttons and forms within the interface allowed the user to easily navigate through the screens and input all required information. The interface was developed to be flexible to be applied to different WDSs as it is able to read in information from a specified EPANET input file to minimize the input effort required by users.

3. Results

The models were applied to a case study network (Fig. 2) that was previously optimized by Wu *et al.* [2] for its physical characteristics but not its operation. This network transferred water from a reservoir to an upstream tank, from which demands were withdrawn, with a base demand of 80 L/s and a diurnal pattern based on the peak residential demands used by the South Australian Water Corporation. A minimum tank water level of 0.3 m was applied to account for dead storage. The lowest possible trigger level value was set to 1.0 m, to allow for times in which the demands exceeded the pump capacity and the highest possible trigger level value was 5.0 m. A sensitivity analysis was performed on various parameters including the objective function, electricity tariff, energy scenario, reduced upper trigger level switch time, the use of FSPs and VSPs, and the carbon cost.

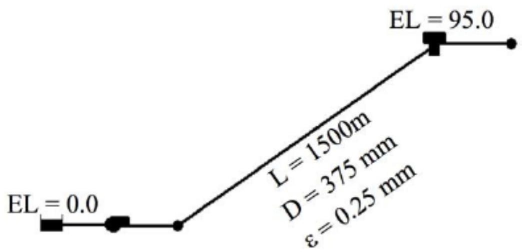

Fig. 2. The one-pipe and one-pump network

Complete enumeration of the lower and upper trigger levels problem was undertaken, confirming the validity of the optimization results obtained from the model. This was possible only because of the small number of decision variables, which meant that the total number of possible solutions was 441. The lower and upper trigger level optimization model found cost optimal solutions were achieved with a lower trigger level of 1.0 m and an upper trigger level of 5.0 m as this solution enabled the maximum off-peak pumping (Table 1). In comparison, the optimal GHG and energy solutions were the same and had lower and upper trigger levels of 1.0 m and 1.2 m respectively. This optimal GHG and energy solution used the smallest possible range to achieve the lowest possible static head, with pumping spread evenly over the entire day. The sixth best solution from the cost optimization represented a trade-off between the cost and GHG objectives. This solution reduced the static head by having an upper trigger level of 2.6 m and half-filled the tank twice during the off-peak period, still taking advantage of the cheaper electricity rate. It required more peak pumping than the best cost solution, however, so was more expensive.

Table 1. Selected solutions from initial analysis

Solution	Lower trigger level (m)	Upper trigger level (m)	Cost ($/m^3)	GHGs (kg CO_2-eq/m^3)	Energy (kWh/m^3)	Peak energy (%)	Off-peak energy (%)
Cost – Best	1.0	5.0	0.0683	0.2217	0.3718	72.0	28.0
Cost – 6th Best	1.0	2.6	0.0697	0.2210	0.3696	75.7	24.3
GHG – Best	1.0	1.2	0.0721	0.2204	0.3685	81.2	18.8

In comparison, when using a flat tariff structure with an energy price of 17.67 c/kWh (the weighted average of the peak and off-peak price), all optimizations found the same solution regardless of which objective function was used. This was the same solution that was found by the GHG and energy optimizations previously, with the two trigger levels as close together as possible. With the flat tariff, this solution had a cost of 0.0651 $/m^3, which was a lower cost than the best cost solution found using the peak/off-peak structure. Because the trigger levels are very close together, the pump turns on and off continually throughout the day (Fig. 3 (a)), with the exception of two blocks where the pump is on from 7am to 9am and 7pm to 11pm due to high demands. These are both during the peak electricity period and hence this solution is very expensive (and therefore not optimal) when evaluated with the peak/off-peak electricity tariff. In practice, this solution may be less appealing to operators as there is a large number of pump switches, and the model allowed this to be taken into account as a constraint if desired by the user.

Applying the various future energy scenarios gave the same optimal solutions as the initial analysis, with one exception. When the percentage of solar photovoltaic energy contribution was relatively high, as it was for the AEMO 'Oil Shock and Adaption' scenario, the solution found by GHG optimization had a much wider trigger level range than was found previously, with trigger levels of 1.0 m and 4.8 m compared to 1.0 m and 1.2 m. The graph of pump flow over 24 hours for this solution (Fig. 3 (b)) shows that the pump was switched on from 9am to 3pm, the time when the solar photovoltaic contribution is highest and the thus emissions factors lowest. This catered to the larger variation in emissions factors throughout the day, due to the increased proportion of solar photovoltaic energy.

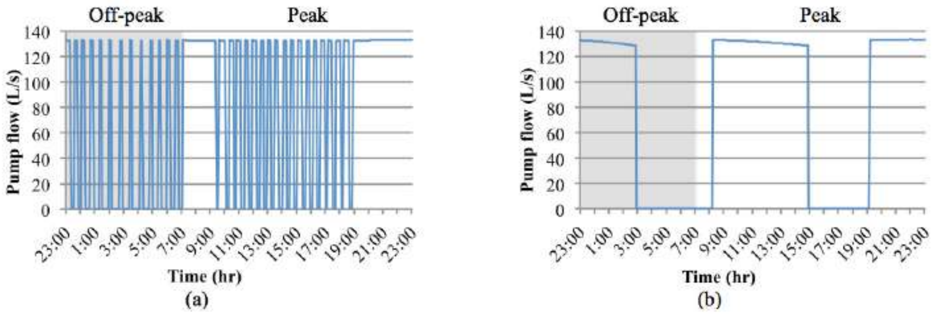

Fig. 3. Daily pump flow variation with trigger levels of (a) 1.0 m and 1.2 m and (b) 1.0 m and 4.8 m

To confirm that the difference in the optimal solutions was a result of the higher percentage of solar photovoltaic energy and not a different aspect of the 'Oil Shock and Adaption' energy scenario, two custom energy scenarios were created. They were based on the 'Oil Shock and Adaption' scenario, with the percentage of solar photovoltaic energy in one scenario increased to 10% and in the other decreased to 1%. The optimal solution found with the higher proportion of solar photovoltaic energy had lower and upper trigger levels of 1.0 m and 5.0 m, while the lower proportion of solar photovoltaic energy resulted in trigger levels of 1.0 m and 1.2 m, confirming that the percentage of solar photovoltaic energy was causing the difference in the results. When a reduced upper trigger level was incorporated into the model, the minimum cost was lowered to 0.0652 \$/m^3, compared to 0.0683 \$/m^3 when only lower and upper trigger levels were used. A switch time of 2am was found to be optimal, as this allowed the tank to completely fill just before the start of the peak period (Fig 4), hence minimizing the amount of pumping required when electricity rates were more expensive. The addition of a reduced upper trigger level did not improve upon the optimal solutions already found for the GHG and energy objectives. This was expected as GHG emissions and energy were minimized by minimizing static head and having the trigger levels very close together, so no additional benefit was achieved by filling the tank.

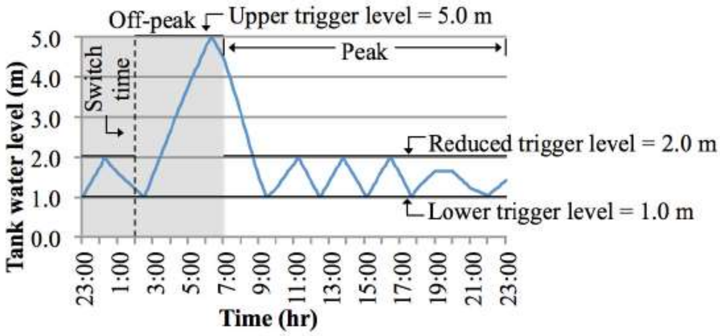

Fig. 4. Daily tank level variation for the optimal cost solution with a reduced upper trigger level

VSP scheduling was found to reduce the cost and GHG emissions of pump operations compared to the trigger levels solutions. An initial run of the scheduling optimization model gave a solution with a cost of 0.0637 \$/m^3 and GHG emissions of 0.2185 kg CO_2-eq/m^3. This solution was able to fill the tank completely before the peak electricity period and had slightly increased pumping over the afternoon period where GHG emissions factors were lowest. Using a FSP with this model found a more expensive solution than for VSPs, with a cost of 0.0656 \$/m^3. The FSP solution was not able to fill completely the tank before the peak period and therefore required more peak pumping and had a higher energy cost.

Table 2. Cost optimal solutions using a peak/off-peak tariff and a flat tariff with scheduling

Tariff	Cost (\$/m^3)	GHGs (kg CO_2-eq/m^3)	Vol. (m^3)	Energy (kWh)	Energy (kWh/m^3)	Max. tank level (m)	Peak energy (%)	Off-peak energy (%)	Peak cost (\$)	Off-peak cost (\$)
Peak/off-peak	0.06274	0.2185	6931	2529	0.3648	4.81	63.1	36.9	351	84
Flat	0.06375	0.2162	6919	2497	0.3608	2.81	73.6	26.4	325	116

When a flat tariff was applied to the scheduling problem, the optimal cost solution was slightly more expensive than that found with the peak/off-peak tariff (Table 2). The optimal scheduling solution with a peak/off-peak tariff was able to pump more in the off-peak period compared to the trigger levels and flat tariff solutions. While the flat tariff solution had a lower energy use and reduced static head, the significant amount of off-peak pumping in the peak/off-peak tariff solution had a greater effect on the cost. The cost of this scheduling solution was much less than the trigger levels solutions presented previously, with the overall and peak period energy use reduced. The optimal operating strategy for the one-pipe network was found using the multi-objective optimization with a carbon cost of 500 \$/ton CO_2-eq. It cost 0.0626 \$/m^3, which is less than any other solution found using the three optimization models and had GHG emissions of 0.2176 kg CO_2-eq/m^3, again less than any solution found using the trigger levels models when the current South Australian energy scenario was used. This solution fulfilled the cost objective by having the tank full at the start of the peak period (Fig. 5 (a)). It also satisfies the GHG objective by pumping more in the afternoon (Fig. 5 (b)), coinciding with the low GHG emissions factor period due to the increased contribution of solar photovoltaic energy. Scheduling was found to provide more flexible operation than trigger levels, as it was able to cater to the variations in both cost and GHG parameters at the same time.

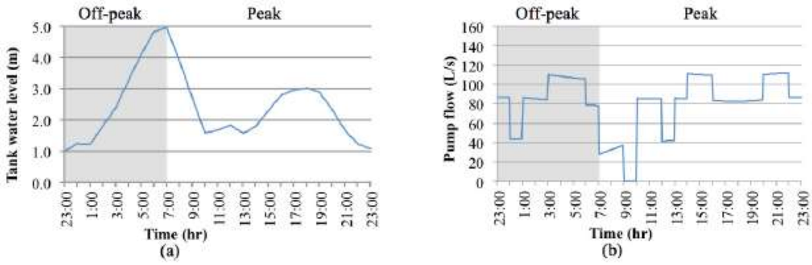

Fig. 5. (a) Daily tank level variation and (b) daily pump flow variation for optimal one-pipe network operation

4. Conclusions

This research developed a GA model to optimize the pumping operation of WDSs for multiple objectives, including cost, energy and GHG emissions. Three distinct optimization models were produced, each incorporating a different operating regime; lower and upper trigger levels, an additional reduced upper trigger level and scheduling. It was found that the use of scheduling improved both cost and GHG emission results compared to the two trigger level regimes. VSP scheduling was more adaptable to varying cost and GHG parameters, and was able to cater to both objectives at the same time. It was shown that GHG and energy objectives did not necessarily coincide when the variation in energy source output was taken into account. The models developed in this research could be applied to pump operation problems on any WDS, particularly through the use of the user-friendly Excel Interface.

Acknowledgements

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Appendix D: Final Published Version of WDSA 2016 Conference Paper

Paper presented at the 18th Conference on Water Distribution Systems Analysis, WDSA 2016 in Cartagena, Colombia.

Formulation of the Pump Operations Optimization Problem for a Harvested Stormwater System

Blinco, L.J., Simpson A.R., Lambert, M.F., and Marchi, A.

School of Civil, Environmental and Mining Engineering

The University of Adelaide, Adelaide, SA 5005 Australia

Procedia Engineering, 186.

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Formulation of the pump operations optimization problem for a harvested stormwater system

Lisa J. Blinco[a,b]*, Angus R. Simpson[a,b], Martin F. Lambert[a,b], Angela Marchi[a,b]

[a]*School of Civil, Environmental and Mining Engineering, Engineering North N136, North Terrace Campus, The University of Adelaide, South Australia 5005, Australia*

[b]*Cooperative Research Centre for Water Sensitive Cities, PO Box 8000, Monash University LPA Clatyon, Victoria 3800 , Australia*

Abstract

As climate change and population growth, among other factors, put pressure on traditional water supplies, alternative sources of water are increasingly being used to supplement demand, particularly for non-potable applications. Stormwater from urban catchments can be harvested and treated to supply irrigation demands of public green spaces such as parks, reserves and sporting grounds. Operation of such systems often requires several pumping stages between multiple storage ponds, which can result in a significant amount of energy use and also increases the complexity of the operations. In many water supply systems, demand rates and patterns are determined by when consumers choose to use water and how much they use, thus the demands constrain the system operation. For irrigation of public green spaces, however, the operators can prescribe when water should be used at each demand point, and thus the demand pattern is a choice rather than a constraint. This paper discusses how harvested stormwater systems with multiple pumping stages can simulated as multiple 'sub-systems' in order to better understand the hydraulics and better formulate the corresponding optimization problem. A case study site from Australia that utilizes harvested stormwater for non-potable irrigation demands is used to demonstrate the simulation approach. Simulating the case study in smaller 'sub-systems' has highlighted the need for better pump and tank sizing for the system, and has then informed the optimization problem formulation.

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Keywords: Water supply systems; optimization; harvested stormwater; pump operation; irrigation scheduling; genetic algorithms

* Corresponding author. Tel.: +618-8313-1575; fax: +618-8313-4359.
E-mail address: lisa.blinco@adelaide.edu.au

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1. Introduction

Genetic algorithms (GAs) have been used extensively to optimize the design and operation of water distribution systems (WDSs) [1]. GAs were first applied to WDSs in 1994 to optimize the design of pipe networks [2] and then to the optimization of WDS operations in the form of pump scheduling [3] and operational set points [4]. GAs, when applied to WDS pump operation, have also shown the benefits of using variable speed pumps (VSPs) to reduce pumping costs and greenhouse gas (GHG) emissions while complying with hydraulic constraints [5]. Multiple objectives may be considered using GAs, and the trade-off between minimizing cost and minimizing GHG emissions has been explored extensively, for example in [6]. GAs are often combined with hydraulic simulation software, such as EPANET2, in order to determine the performance of selected WDS designs and operational strategies with regard to the objectives. Recently, the capability of the EPANET2 Programmer's Toolkit has been extended so that rule-based controls can be optimized, greatly increasing the complexity and flexibility of operating rules that can be considered in a GA optimization procedure [7].

Alternative sources of water, including harvested stormwater, are increasingly being used to supplement potable demand, particularly for non-potable applications [8]. As such systems become more popular, simulation and optimization methods should be adapted to allow consideration of alternative water sources. This introduces additional complexity to the problem of simulation and optimization than has been previously considered for traditional water systems [9]. Harvested stormwater systems often have multiple storage ponds, with pumps transferring water at each stage; this requires significant energy use, and as the pumps may not operate at the same flow rate, can increase the complexity of operations. These systems are also often combined with aquifer storage and recovery, which can also contribute significantly to energy use due to high pumping heads when injecting into and extracting from aquifers. Optimization of the pump operations of these system can therefore be used to provide significant savings in energy costs. When used for irrigation applications, demand schedules may also be optimized to minimize pumping costs and improve hydraulic performance. GAs have previously been applied to harvested stormwater systems, for example [10], however not for the optimization of detailed hydraulic operations.

2. Case Study: Ridge Park Managed Aquifer Recharge System

The case study system, located in Adelaide, South Australia, collects stormwater from an urban creek to recharge an aquifer, which then supplies water for irrigation of local reserves. The simulation and optimization of the system can be split into two sections separated by the aquifer storage; winter operation (harvesting and aquifer injection) and summer operation (aquifer extraction and irrigation). During winter operation, water is collected from Glen Osmond Creek in the harvest pond, pumped to the bioretention basin, pumped through a small treatment plant (consisting of a micro-filter and a UV disinfectant system) into the storage tank, and finally pumped into the aquifer (Fig. 1). During summer, water is extracted from the aquifer, stored in the same tank used during winter, and then supplied to the irrigation sites either by gravity or pumping (Fig. 2). Pump 3, shown in Fig. 1 and Fig. 2, is used for both injection into the aquifer and irrigation and is a variable speed pump (VSP). In order to develop an accurate hydraulic model of the system, it was first simulated as seven smaller 'sub-systems' in EPANET hydraulic simulation software:

- Sub-System 1: Pump 1 from the harvest pond to bioretention basin
- Sub-System 2: Pump 2 from the bioretention basin to storage tank
- Sub-System 3: Pump 3 injection from the storage tank to the aquifer
- Sub-System 4: Pumps 1, 2 and 3 from the harvest pond to aquifer injection
- Sub-System 5: Bore pump extraction from the aquifer to the storage tank
- Sub-System 6: Pump 3 irrigation from the storage tank to the pressure irrigation system
- Sub-System 7: Irrigation from the storage tank to both the pressure and gravity systems

2.1. Simulation of non-typical components

The Ridge Park system includes several components that are not typically included in traditional water distribution systems and therefore do not have a direct representation in EPANET, such as natural waterways, bioretention basins, small treatment plants and aquifer injection/extraction. Glen Osmond Creek was represented as a node connected to the harvest pond by a frictionless pipe (short, large diameter and small roughness height), with the inflow series applied as a demand pattern and a negative base demand. The harvest pond and bioretention basin were both simulated as tanks, with a volume curve applied to the bioretention basin to take into account the porosity of the filter media. Pressure sustaining valves were added before both the bioretention basin and storage tank to simulate the pipes discharging over the top of these storages. A general purpose valve was used to represent the losses through the treatment process, with a headloss curve applied to increase the headloss across the valve as the flow increased.

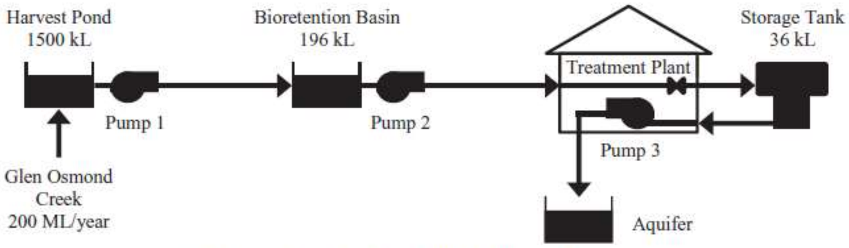

Fig. 1. Ridge Park winter harvesting and injection schematic

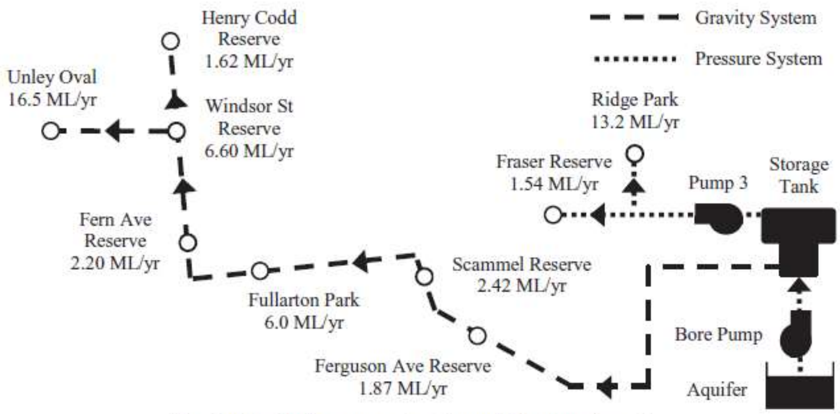

Fig. 2. Ridge Park summer extraction and irrigation schematic

The most difficult component to represent in EPANET is the aquifer injection and extraction process. While the aquifer itself can be easily represented as a reservoir, the variation in the aquifer head and headloss through the bore with time are harder to model. When injecting, the standing water level of the aquifer increases by roughly 45 m over 1 to 2 hours (at the maximum injection rate of 7 L/s). Once injection stops, the level will decrease approximately half way back to the normal standing level over 1 to 2 hours, and then gradually decreases the rest of the way over 24 hours. When extracting, the standing water level drops down to just above the height of the pump (40 m below ground) over seven days. Once extraction stops, it will recover most of the way within an hour, with the last 1 to 2 metres recovered gradually over approximately 12 hours. The bore will start to clog during injection, and the rate that this occurs will depend on the turbidity of the water. As the bore clogs, the pump speed will reduce, maintaining 45 m of head while reducing the flow rate. Once the flow is reduced to around 4.5 L/s (which is half of the maximum injection rate), a backwash will be initiated to unclog the bore. If a maximum turbidity of 5 NTU is applied (water that does not meet this constraint is then recirculated), this backwashing should occur roughly once every week. In addition to this, there will be some resistance during injection due to water having to pass by the bore pump (this head loss should be in the order of 2-3 m). The aquifer is represented as a reservoir, with total head at 45 m above the standing water level for injection, and a total head 5 m above the bore pump elevation for extraction. Just before the aquifer, a pressure breaker valve (PBV) was added, to simulate both the minor loss due to the pump and losses due to clogging.

2.2. Important results from sub-systems analysis

The maximum permissible flow for aquifer injection (and therefore Pump 3 during winter operation) is 7 L/s, while Pumps 1 and 2 operate at much higher flows. Analysis of the system curves (Fig. 3) shows that Pump 1 will operate at around 22 L/s, and Pump 2 at around 26 L/s, and this was confirmed when Sub-Systems 1 and 2 were analyzed in EPANET. This problem came about because the system was first designed with two injection bores, which would have doubled the injection rate to 14 L/s. If there was a significant storage between Pumps 2 and 3, water could be harvested when rainfall and runoff occurred, and stored before injecting during off-peak electricity times. The largest storage in the system, however, is the harvest pond, which is at the start of the harvesting process, upstream of Pump 1. This means that the pumps turn on and off frequently, as it does not take long to fill and empty the storages between the trigger levels (Fig. 4 shows an example for Pump 1). Also contributing to this is the fact that the storages are not large, in particular the storage tank. The full volume of this tank is under-utilized; during commissioning pump priming issues occurred when the tank level was below 60%, the cause of which was never properly resolved. The current trigger levels in this tank, at 70% and 90% of the volume, restrict the operational range even further. Therefore only 7.2 kL (out of 36 kL) is available; with Pump 2 operating at 26 L/s and Pump 3 at 7 L/s, it takes less than 10 minutes to fill this volume.

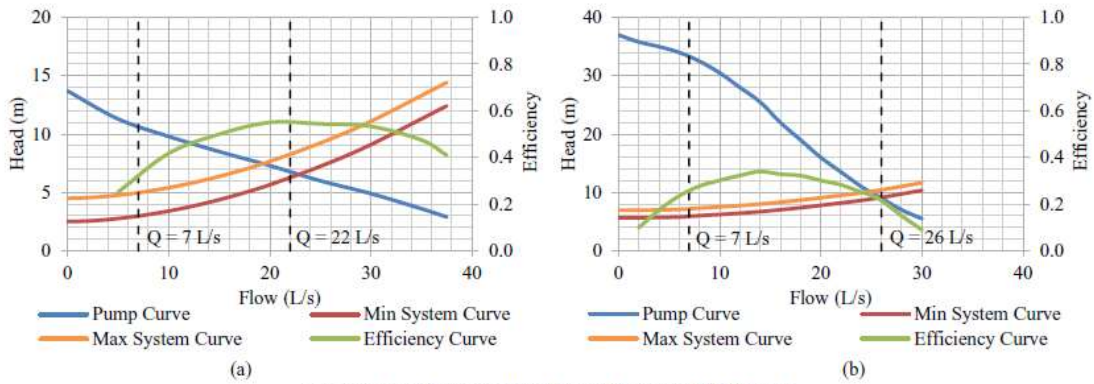

Fig. 3. Pump and system curves for (a) Pump 1 and (b) Pump 2

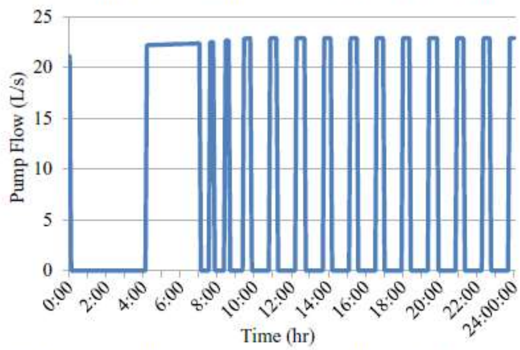

Fig. 4. Example of Pump 1 operations over 24 hours in Sub-System 1

Sub-System 3 was used to test VSP multipliers for Pump 3 and headloss values through the bore. Fig. 5 shows how the EPANET model for Sub-System 3 was set up, with a PBV added upstream of the aquifer, allowing headloss due to water being injected around the bore pump and clogging of the bore to be taken into account. The head of the aquifer was specified at 45 m above its standing water level (which is the expected impressed level during injection). The headloss caused by the bore pump is roughly 2-3 m, and therefore the minimum headloss applied over the PBV is 2.5 m. The speed of the pump was adjusted to find a maximum operating flow of 7 L/s, this occurred with a speed of 0.78 providing 6.78 L/s. Assuming the turbidity of the water is kept below 5 NTU, it is expected the bore backwash at a flow of 4.5 L/s will occur once a week (as discussed in Section 2.1). The headloss value of the PBV was altered to produce a flow rate of around 4.5 L/s at the previously determined speed of 0.78. A flow rate of 4.94 L/s was achieved with a PBV value of 4.3 m (an additional 1.8 m). The PBV value should therefore range from 2.5 m to 4.3 m over the course of one week (increase of 0.3 m each day). Head patterns can be applied to the aquifer for both injection and extraction to consider the change in aquifer head over time (including seasonal variation).

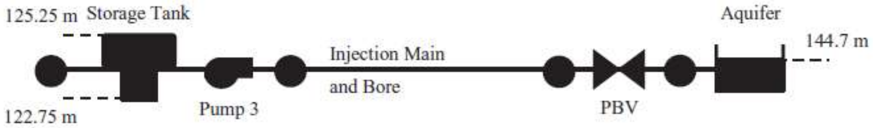

Fig. 5. Schematic of Sub-System 3 representation in EPANET

Poor efficiency of the pumps resulted in high electricity operating costs, for Pumps 2 and 3 in particular, when analyzing Sub-Systems 1 to 4. Table 1 shows the flow, head, efficiency and cost of pumping at the operating points determined from analysis of Sub-Systems 1 to 3, as well as the best efficiency for each pump. The power consumption (P, in kW) of each pump is calculated based on Equation 1 (with specific weight $\gamma = 9810$ N/m^3, Q = flow [m^3/s], H = head [m] and η = efficiency). Assuming each pump is run for an hour (as an indicative example), the energy use (in kWh) and volume pumped (in ML) can be calculated, which allows the calculation of the cost of pumping (in $/ML) based on an average electricity price of 23.3 cents/kWh. Pump 1 operates close to its best efficiency point and at a high flow rate, which results in a comparably small cost of pumping. The efficiency of Pump 2 is very low across all flow rates, and therefore regardless of its operating point, it will have a low efficiency and a higher cost than Pump 1. In addition, Pump 3 does not operate close to its best efficiency point, even with variable speed pumping (the data shown in Table 1 is for a relative pump speed multiplier of 0.78). The low flow rates for this pump also contribute to a much higher cost of pumping than Pumps 1 and 2.

$$P = \frac{\gamma QH}{1000 * \eta} \tag{1}$$

Table 1. Operating point, efficiency and cost data for Pumps 1, 2 and 3 for 1 hour of operation only

	Flow (L/s)	Head (m)	Efficiency (%)	Efficiency$_{max}$ (%)	Cost ($/ML)
Pump 1	22.9	6.55	54.4	55.0	7.63
Pump 2	26.0	8.98	21.5	33.9	26.5
Pump 3 – minimum head loss	6.78	45.4	56.7	71.8	50.8
Pump 3 – maximum head loss	4.94	46.7	45.9	71.8	64.5

3. Optimization Problem Formulation

Both rule-based controls and demand scheduling will be optimized for this case study. A new EPANET programmer's toolkit, ETTAR [7], will be incorporated to allow rule-based controls to be considered. An example of rule-based controls in EPANET is shown below, combining trigger levels and scheduling. These rules require the pump to be off during the peak electricity tariff period (7am-9pm), and allows the pump to operate during the off-peak period if there is water available in an upstream tank. Using ETTAR, any part of these rules can be optimized; the logical operator (if, and, or), the object (e.g. system, tank, pump), the variable (e.g. clocktime, level), the relational operator (e.g. greater than, lower than), the status (open, closed) or the value of the variable. For more details on how these rules can be formulated as decision variables in an optimization problem, see [7].

RULE 1
IF SYSTEM CLOCKTIME >= 7 AM
AND SYSTEM CLOCKTIME < 9 PM
THEN PUMP 1 STATUS IS CLOSED

RULE 2
IF SYSTEM CLOCKTIME < 7 AM
OR SYSTEM CLOCKTIME >= 9PM
AND TANK 1 LEVEL ABOVE 1.0
THEN PUMP 1 STATUS IS OPEN

The demand scheduling decision variables include the demand start day and demand start time, with other irrigation scheduling variables to be specified in the optimization input file (Table 2). Values in the choice table for the potential start days should be integers, with 0 being the first day of the EPANET simulation. For example, if the choice table held values of 1 and 2, and the EPANET simulation started on Sunday, this would mean the first irrigation event could occur on either Monday or Tuesday. With a gap of 1 day, and number of events of 2, this means that irrigation would either occur on Monday and Wednesday, or Tuesday and Thursday. Values in the choice table for the potential start time should be in decimal hours, for example, 21.00, 21.50, 22.00, 22.50 (9pm, 9:30pm, 10pm, 10:30pm), and so on. An example decision variable string for a system with two pump/tank combinations and two irrigation demands to optimize is shown in Fig. 6 (not related to the Ridge Park Case Study previously discussed), with respect to the example choice tables shown in Table 3. The '0' in the first gene for each pump/tank combination shows that a lower trigger level value of 0.5 m has been selected (from Choice Table 1 in Table 3). For the second gene for the pump/tank combinations, the '2' and the '3' would represent values of 1.5 m and 2.0 m respectively for the upper trigger levels. For the demand genes, the '0' for the first demand start day represents the first irrigation day being Monday, and the '1' for the second demand start day being Tuesday (from Choice Table 2 in Table 3). The '0' for the first demand start time represents the earliest possible start time of 21.00 (9pm), while the '3' for the second demand start time would be 22.50 (10:30pm) (from Choice Table 3 in Table 3).

Table 2. Information needed to specify demand scheduling decision variables in optimization input file

Parameter	Description
Pattern Index	The EPANET index of the demand pattern that is to be changed
Duration	The duration of the irrigation on each day that irrigation occurs (decimal hours)
Gap	The gap between irrigation days (for example, for irrigation every second day, the gap would be 1)
Number of Days	The number of days to irrigate per week
Day Choice Table	The choice table for the day of the week that irrigation starts on
Time Choice Table	The choice table for the time of day that irrigation starts

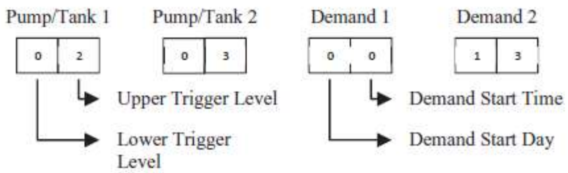

Fig. 6. Example string for optimizing trigger levels and irrigation schedules (with respect to choices in Table 3)

Table 3. Example choice tables for optimizing trigger level and irrigation schedule decision variables in Fig. 6

Integer Value	Choice Table 1 Trigger Level (m water depth in tank)	Choice Table 2 Demand Start Day	Choice Table 3 Demand Start Time (hr)
0	0.5	Monday	21.00
1	1.0	Tuesday	21.50
2	1.5	Wednesday	22.00
3	2.0	Thursday	22.50

3.1. Decision variables for the Ridge Park Case Study

There are eight trigger level decision variables for the winter operations of the system as shown in Table 4. The summer operations of the system has two trigger level decision variables and eleven irrigation demand decision variables as shown in Table 5. Pump 3 does not have any associated decision variables relating to the aquifer in the harvest system as it is run based on pressure at the injection point. It is also run based on a set pressure (that cannot be changed) for the demands to Ridge Park and Fraser Reserve and therefore does not have associated decision variables for the irrigation system. The gap between irrigation days for all reserves is 1 (irrigate every second day).

Table 4. Winter (harvest and injection system) operational decision variables

Decision Variable	Pump	Tank/Storage	Trigger Level Type	Choices
1	1	Harvest Pond	Lower/Off	0.1-2.0m, 0.1m increment
2	1	Harvest Pond	Upper/On	
3	1	Bioretention Basin	Upper/Off	0.1-1.3m, 0.1m increment
4	2	Bioretention Basin	Lower/Off	
5	2	Bioretention Basin	Upper/On	
6	2	Storage Tank	Upper/Off	0.1-2.5m, 0.1m increment
7	3	Storage Tank	Lower/Off	
8	3	Storage Tank	Upper/On	

Table 5. Summer (extraction and irrigation system) operational decision variables

Decision Variable	Pump	Tank/Storage	Trigger Level Type	Choices
1	Bore	Storage Tank	Lower/On	0.1-2.5m, 0.1m increment
2	Bore	Storage Tank	Upper/Off	
Decision Variable	Reserve	Duration (hrs)	Number of Days	Choices
3	Ridge Park (Stations 1-10)	8.33	2	Start Day: Monday or Tuesday
4	Ridge Park (Stations 11-24)	11.67	2	
5	Fraser Reserve	5.83	2	Start Time: 8pm-11:30pm, 30min increment
6	Ferguson Ave Reserve	5.00	2	
7	Scammell Reserve	6.00	2	
8	Windsor St Linear Reserve	8.00	2	
9	Fullarton Park (Stations 5&12)	1.66	2	
10	Fullarton Park (Stations 1-4,6-8)	6.66	2	
11	Henry Codd Reserve	8.00	2	
12	Fern Ave Reserve	3.33	2	
13	Unley Oval	11.33	3	Start Day: Sunday
				Start Time: as above

Several design decision variables are also to be considered. As identified in Section 2.2, the operation of the system has issues with regard to pump sizing and efficiency, as well as frequent pump switches. Sizing of the pumps and the storage tank will therefore also be considered in the optimization. Several pump curves that will operate around 7 L/s at the required head will be specified as possible choices for Pumps 1 and 2. With these pumps operating at a lower speed, the flow through the system will be more consistent, and hence they will not need to turn on and off as frequently. There will also be a choice to either keep the storage tank at its current size, or to double its size. This, along with considering trigger levels that utilize the full height of the tank (assuming the priming issues are resolved), should allow the pumps to turn on and off less frequently. Sizing of Pump 3 will also be considered in the optimization.

As it was originally designed to supply two bores, the best efficiency occurs closer to 14 L/s than 7 L/s. Both VSPs and fixed speed pumps (FSPs) will be considered for Pump 3, with a lower flow range and best efficiency point closer to the desired operating points. As the head and flow requirements for injection and irrigation are similar, a FSP may be suitable for Pump 3. Sizing of the bore pump will not be considered, as while the head range is higher than needed for extraction, this pump is also used to backwash the bore when injecting which may have a significantly higher head requirement. A PSV is used downstream of the bore so that the bore pump runs at a reasonable operating point when extracting. This PSV setting may be considered as a decision variable for the optimization. The primary objective for this case study is to minimize the cost of pump energy use. It is also desirable to maximize the volume of water harvested, which can either be considered as a second objective in a multi-objective optimization, or combined with the cost objective by minimizing the pump energy cost per volume harvested (that is, minimize $/ML).

4. Conclusions

Alternative water source systems have increased complexity for hydraulic simulation and optimization of pump operations compared to traditional WDSs. In order to obtain meaningful optimization results, the hydraulic simulation model of a system should be as accurate as possible. Splitting the system into multiple 'sub-systems' and simulating these individually can provide a better understanding of how the system works and help to formulate the optimization problem. Unforeseen changes to the system, for example, halving the number of bores and therefore the injection rate, or problems during commissioning, such as storage levels needing to be kept within restricted ranges, affect the operation of the system and can mean that design decision variables should be considered as well as operational decision variables. For the Ridge Park case study presented, and for other similar systems, irrigation demands can be optimized as decision variables, rather than being a constraint or unknown variable in the problem.

Acknowledgements

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Appendix E: Ridge Park Managed Aquifer Recharge System Data

E1: Harvesting & Injection System

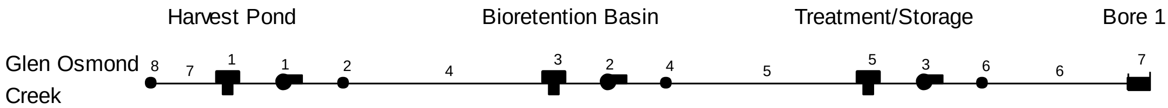

Figure E.1: Schematic of the Harvest/Injection System

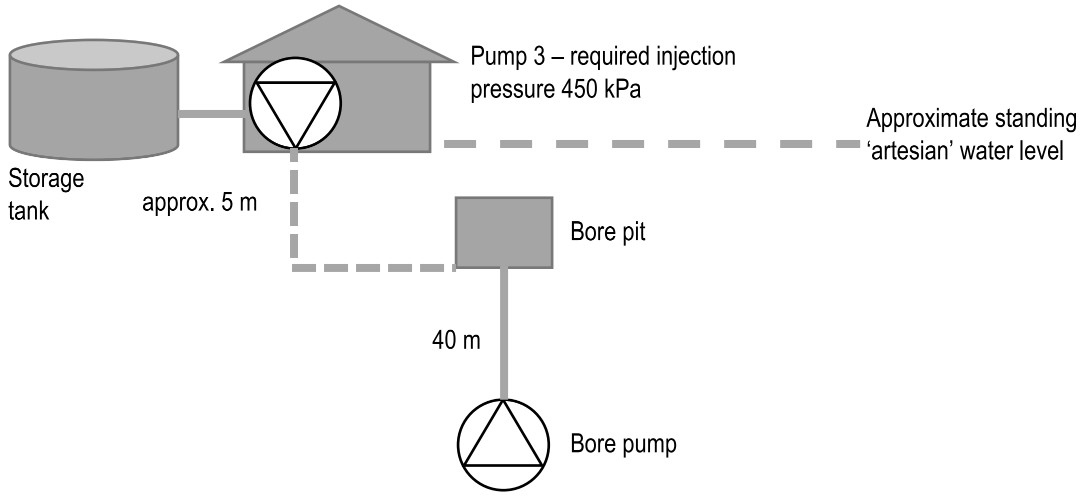

Figure E.2: Schematic of the Aquifer Injection and Extraction System

Table E.1: Hydraulic Simulation Model Node Data for the Harvest/Injection System

Node ID	Elevation (m)	Height (m)	Diameter (m)	Capacity (kL)
Junction 2	117.82	-	-	-
Junction 4	120.68	-	-	-
Junction 6	122.75	-	-	-
Junction 8	116	-	-	-
Reservoir 7 (Aquifer)	170.25	-	-	-
Tank 1 (Harvest Pond)	115	2.0	30.9	1500
Tank 3 (Bioretention Basin)	118.3	1.3	18.88	364
Tank 5 (Storage Tank)	122.75	2.5	4.28	36

Table E.2: Hydraulic Simulation Model Pipe Data for the Harvest/Injection System

Pipe ID	Length (m)	Diameter (mm)	Roughness (mm)	Minor Loss Coefficient
4	101	110	0.0015	-
5	22.5	110	0.0015	20
6	31.5	90	0.0015	-
7*	1	1000	0.000001	-

*Pipe 7 is a short, large diameter pipe with negligible roughness such that is essentially frictionless.

Table E.3: Pump 1 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	13.7	-
5	11.3	25.1
10	9.8	41.7
15	8.5	49.9
20	7.3	55.0
25	6.0	54.4
30	4.9	53.3
35	3.6	47.5
37.5	2.9	41.0

Table E.4: Pump 2 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	37.0	-
2	35.8	9.9
4	35.0	17.4
6	34.0	23.5
8	32.5	27.7
10	30.5	30.2
12	28.0	32.3
14	25.5	33.9
16	22.0	32.8
18	19.0	32.2
20	16.0	30.1
22	13.5	28.2
24	11.0	25.1
25	10.0	23.8

Table E.5: Pump 3 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	80.0	-
2.8	78.5	23.7
5.6	77.5	42.2
8.3	75.0	55.6
11.1	72.0	63.9
13.9	67.5	69.3
16.7	62.0	71.0
17.8	59.8	71.8
19.4	55.0	69.8
22.2	47.0	66.0
23.6	42.5	62.4

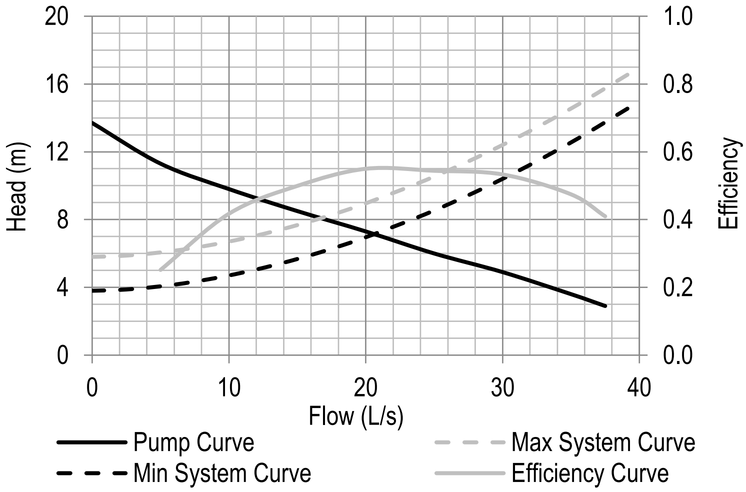

Figure E.3: Pump 1 – Pump, System and Efficiency Curves

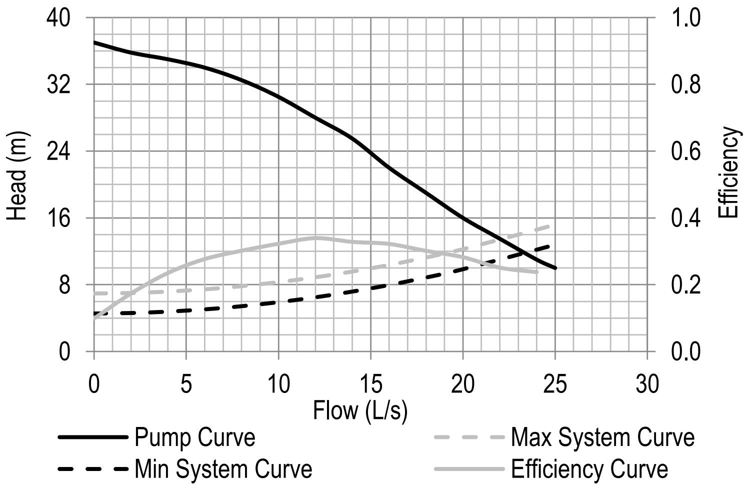

Figure E.4: Pump 2 – Pump, System and Efficiency Curves

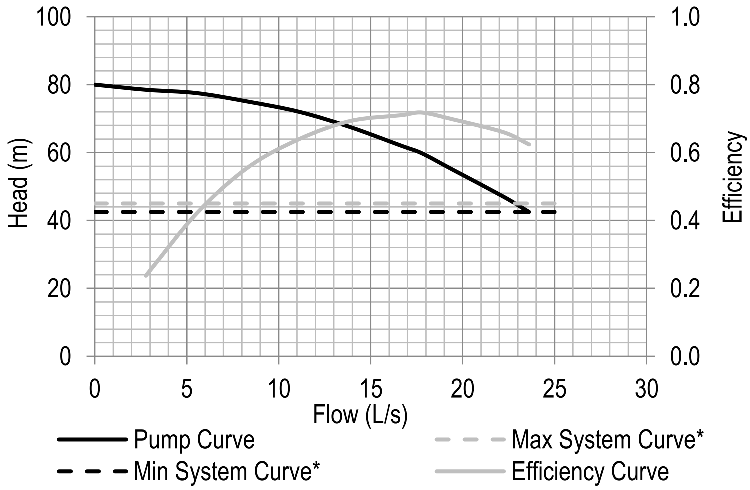

Figure E.5: Pump 3 – Pump, System and Efficiency Curves

*Pump 3 is operated to achieve 45 m of head on the discharge side of the pump, therefore the system head ranges between 42.5 m and 45 m depending on the water level in the storage tank, with no friction losses considered.

Table E.6: Pump Data at Expected Operating Points (for Average System Curve)

Pump	Fig. 1 ID	VSP Speed	Flow (L/s)	Head (m)	Efficiency (%)
Pump 1	1	N/A	18.8	7.6	54.2
Pump 2	2	N/A	22.7	12.6	24.5
Pump 3*	3	0.78	7.0	45.2	57.6

*Pump 3 is limited to 7 L/s for aquifer injection and is therefore operated at a reduced speed (see Figure E.Figure E.6)

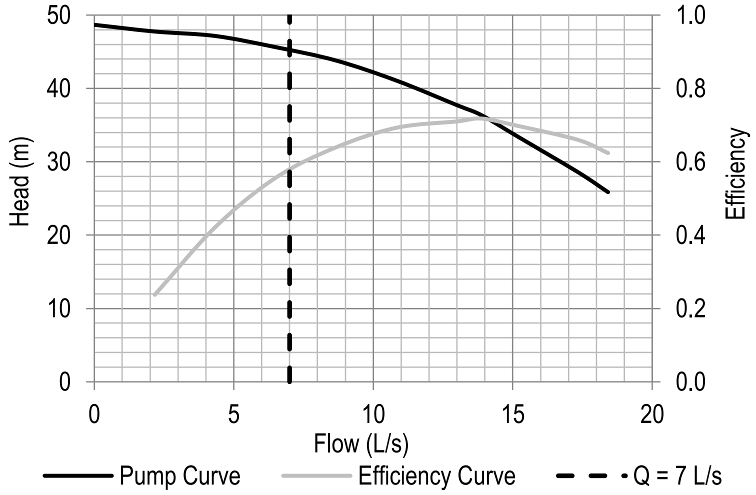

Figure E.6: Pump 3 Reduced Speed (0.78) Pump and Efficiency Curves

E2: Extraction & Irrigation System

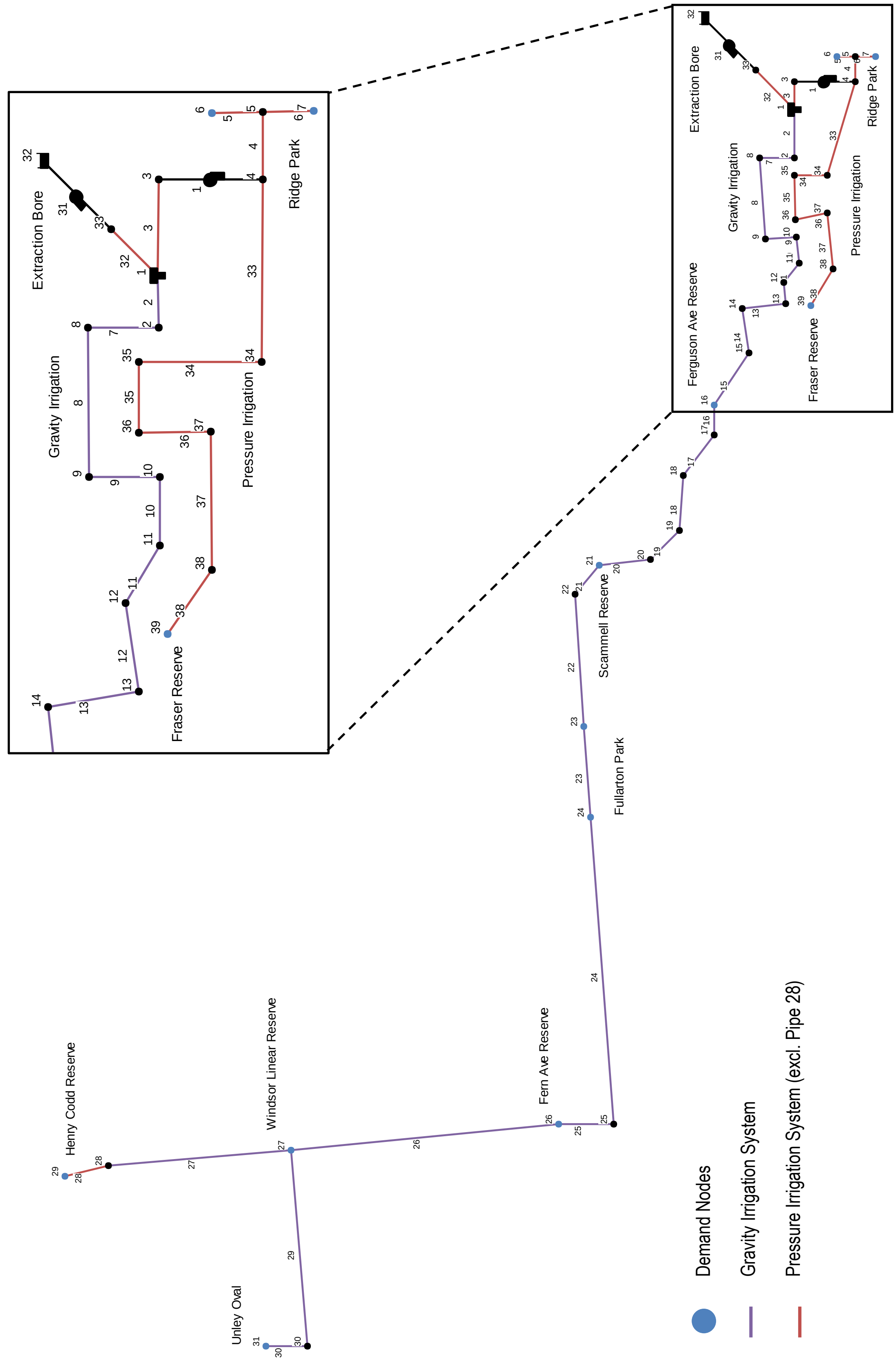

Figure E.7: Schematic of the Extraction/Irrigation System

Table E.7: Hydraulic Simulation Model Node Data for the Extraction/Irrigation System

Node ID	Elevation (m)	Base Demand (L/s)
Junction 2	121.948	-
Junction 3	122.055	-
Junction 4	122.055	-
Junction 5	125.33	-
Junction 6 (Ridge Park Stations 1-10)	125.33	3.53
Junction 7 (Ridge Park Stations 11-24)	125.33	3.53
Junction 8	116.496	-
Junction 9	110.992	-
Junction 10	110.564	-
Junction 11	109.799	-
Junction 12	108.125	-
Junction 13	106.67	-
Junction 14	104.788	-
Junction 15	101.364	-
Junction 16 (Ferguson Ave Reserve)	97.846	2.00
Junction 17	95.563	-
Junction 18	92.258	-
Junction 19	89.209	-
Junction 20	85.612	-
Junction 21 (Scammell Reserve)	83.773	2.15
Junction 22	81.648	-
Junction 23 (Fullarton Park Stations 5&12)	70.045	3.85
Junction 24 (Fullarton Park Stations 1-8)	74.964	3.85
Junction 25	57.173	-
Junction 26 (Fern Ave Reserve)	56.228	3.53
Junction 27 (Windsor St Linear Reserve)	53.096	2.2
Junction 28	51.446	-
Junction 29 (Henry Codd Reserve)	51.273	1.1
Junction 30 (Unley Oval Boundary)	47.913	5.57
Junction 31 (Unley Oval)	47.8	5.57
Junction 33	119.69	-
Junction 34	121.948	-
Junction 35	116.496	-
Junction 36	110.992	-
Junction 37	110.564	-
Junction 38	109.799	-
Junction 39 (Fraser Reserve)	108.125	1.41
Reservoir 32 (Aquifer)	82.75	-
Tank 1 (Storage Tank)*	122.75	-

*Tank 1 dimensions are as shown in Table E.1 (Node ID 5).

Table E.8: Hydraulic Simulation Model Pipe Data for the Extraction/Irrigation System

Pipe ID	Length (m)	Diameter (mm)	Roughness (mm)	Minor Loss Coefficient
2	5.5	180	0.0015	-
3	2.5	90	0.0015	-
4	124.5	90	0.0015	-
5	1	1000	0.0015	-
6	1	1000	0.0015	-
7	77.5	180	0.0015	-
8	270	180	0.0015	-
9	64.652	180	0.0015	-
10	53.3	180	0.0015	-
11	51.332	180	0.0015	-
12	44.724	180	0.0015	-
13	91.069	180	0.0015	-
14	92.725	180	0.0015	-
15	137.979	180	0.0015	-
16	65.853	180	0.0015	-
17	103.598	180	0.0015	-
18	109.702	180	0.0015	-
19	95	180	0.0015	-
20	108.829	180	0.0015	-
21	76.827	180	0.0015	-
22	276.094	180	0.0015	-
23	188.475	180	0.0015	-
24	624.775	180	0.0015	-
25	115.398	180	0.0015	-
26	559.602	180	0.0015	-
27	375	180	0.0015	-
28	100	90	0.0015	-
29	70.206	180	0.0015	-
30	60	180	0.0015	-
32	31.5	90	0.0015	60
33	5.5	90	0.0015	-
34	77.5	90	0.0015	-
35	270	90	0.0015	-
36	64.652	90	0.0015	-
37	53.3	90	0.0015	-
38	51.332	90	0.0015	-

Table E.9: Pump 3 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	80.0	-
2.8	78.5	23.7
5.6	77.5	42.2
8.3	75.0	55.6
11.1	72.0	63.9
13.9	67.5	69.3
16.7	62.0	71.0
17.8	59.8	71.8
19.4	55.0	69.8
22.2	47.0	66.0
23.6	42.5	62.4

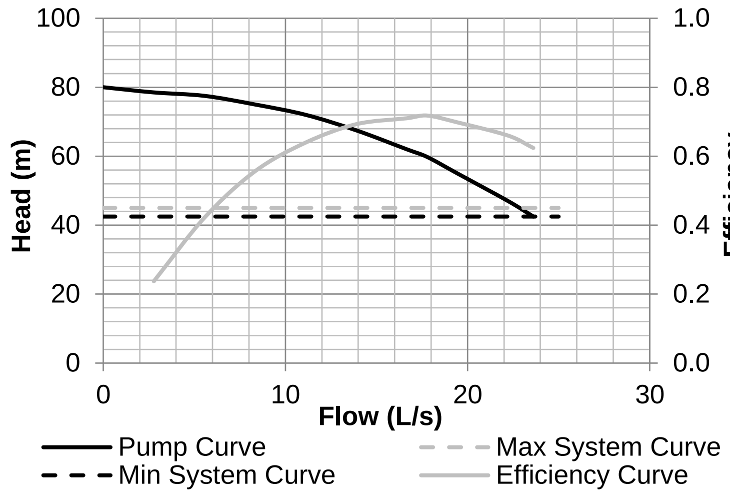

Figure E.8: Pump 3 – Pump, System and Efficiency Curves

Table E.10: Bore Pump – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	99.0	-
2.78	97.0	20.3
5.56	92.0	36.3
8.33	83.0	48.4
11.11	72.0	56.0
13.89	63.0	61.2
16.67	53.0	60.9
19.42	40.4	54.5
19.44	40.0	54.4
21.67	26.0	40.9

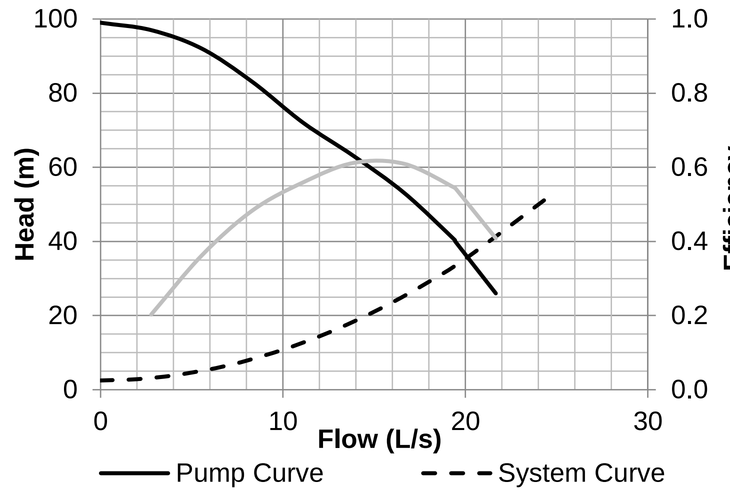

Figure E.9: Bore Pump – Pump, System and Efficiency Curves

Table E.11: Pump Data at Expected Operating Points (at Average System Curve / Demand Scenario)

Pump	Fig. 7 ID	VSP Speed	Flow (L/s)	Head (m)	Efficiency (%)
Pump 3*	1	0.77	4.86	45.6	45.8
Bore Pump	31	N/A	20.1	35.7	50.5

*Pump 3 supplies the irrigation demands directly so will operate at the flow required by the demands, a reduced speed is used to reduce pumping head and therefore reduced energy use.

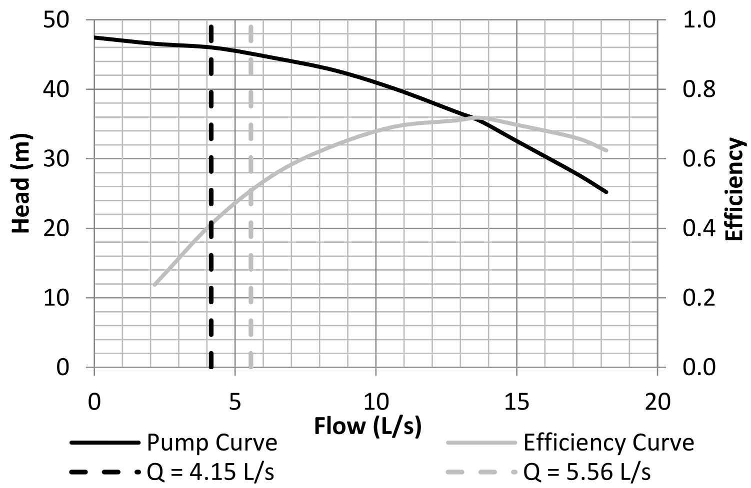

Figure E.10: Pump 3 Reduced Speed (0.77) Pump and Efficiency Curves

E3: Other Data

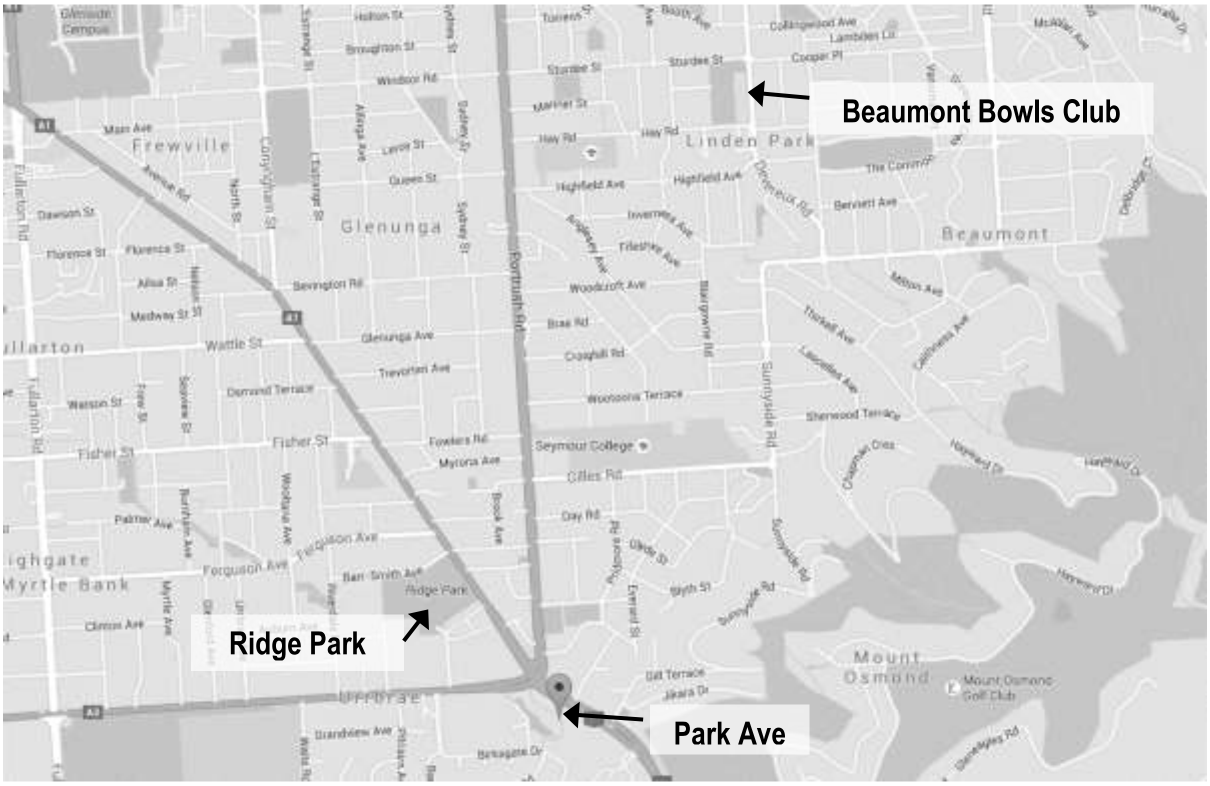

Figure E.11: Map of Locations of Rainfall and Streamflow Measuring Points for Ridge Park, located in Myrtle Bank, a suburb of Adelaide, South Australia

Table E.12: Summary of Rainfall and Streamflow Data Available

Location	Organisation	Start Date	End Date	Data Type
Ridge Park, Myrtle Bank, South Australia	Bureau of Meteorology, Australia	26/03/98	15/01/01	Sub-daily Rainfall
Ridge Park, Myrtle Bank, South Australia	Bureau of Meteorology, Australia	29/10/06	11/11/15	Sub-daily Rainfall
Ridge Park, Myrtle Bank, South Australia	Bureau of Meteorology, Australia	29/10/06	02/01/12	Watercourse level
Park Ave, Urrbrae, South Australia	Dept. of Environ, Water and Natural Resour., South Australia	09/08/98	06/07/01	Streamflow
Beaumont Bowls Club, Linden Bark, South Australia	Bureau of Meteorology, Australia	1883	Present	Daily Rainfall

Table E.13: Electricity Tariff Data

Tariff	Times	Rate (c/kWh)
Peak	7am-9pm Weekdays	29.12
Off-peak	9pm-7am Weekdays, Weekends	15.07

Appendix F: Orange Integrated Supply System Data

F1: Surface Water

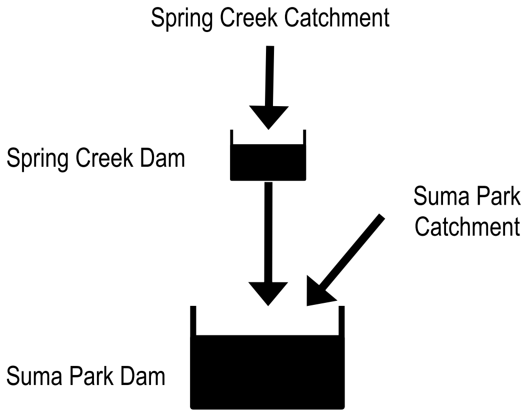

Figure F.1: Schematic of the Natural Catchment

Table F.1: Catchment Data for the Surface Water System

Catchment	Area (ha)	Inflow
Spring Creek Catchment	65.57	MUSIC Generated Streamflow – see Section 5
Suma Park Catchment	112.92	MUSIC Generated Streamflow – see Section 5

Table F.2: Storage Data for the Surface Water System

Storage	Elevation (m)	Capacity (ML)	Surface Area (ha)
Spring Creek Dam	~900	4449	97.5
Suma Park Dam	861.2	18 970	159.5

Table F.3: Spring Creek Volume Curve

Depth (m)	Capacity (ML)	Surface Area (ha)
0	6.950	0
0.5	23.30	2.01
1.0	40.19	4.02
1.5	80.07	6.03
2.0	122.1	8.04
2.5	197.7	10.05
3.0	275.4	12.06
3.5	388.5	14.08
4.0	503.7	21.73
4.5	651.7	28.01
5.0	802.0	33.53
5.5	987.0	38.56
6.0	1175	38.56
6.5	1407	47.61
7.0	1642	51.76
7.5	1934	55.72
8.0	2230	63.18
8.5	2592	70.15
9.0	2957	73.48
9.5	3396	82.98
10.0	3839	88.97
10.6	4449	97.52

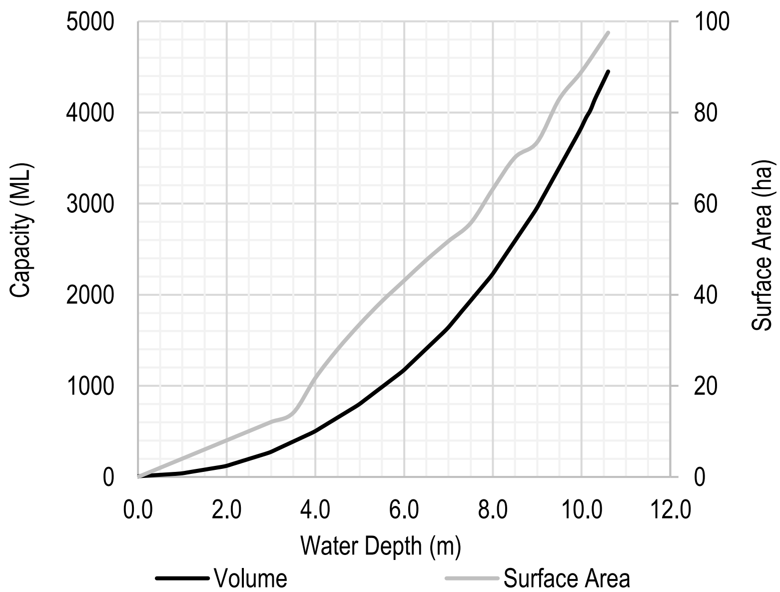

Figure F.2: Spring Creek Volume Curve

Table F.4: Suma Park Volume Curve

Depth (m)	Capacity (ML)	Surface Area (ha)
0.19	2500	49.15
1.19	3025	51.63
2.19	3590	55.15
3.19	4193	59.68
4.19	4842	65.21
5.19	5533	71.53
6.19	6270	78.70
7.19	7072	85.37
8.19	7938	96.19
9.19	8866	105.0
10.19	9857	114.7
11.19	10927	120.9
12.19	12084	134.5
13.19	13332	148.0
14.19	14667	158.3
15.19	16079	160.3
16.00	17293	165.0
17.00	18970	-

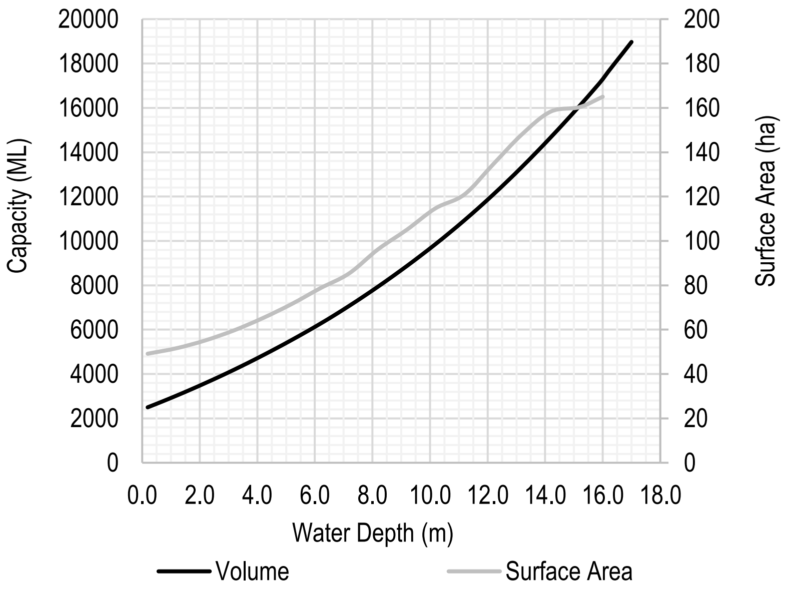

Figure F.3: Suma Park Volume Curve

F2: Stormwater

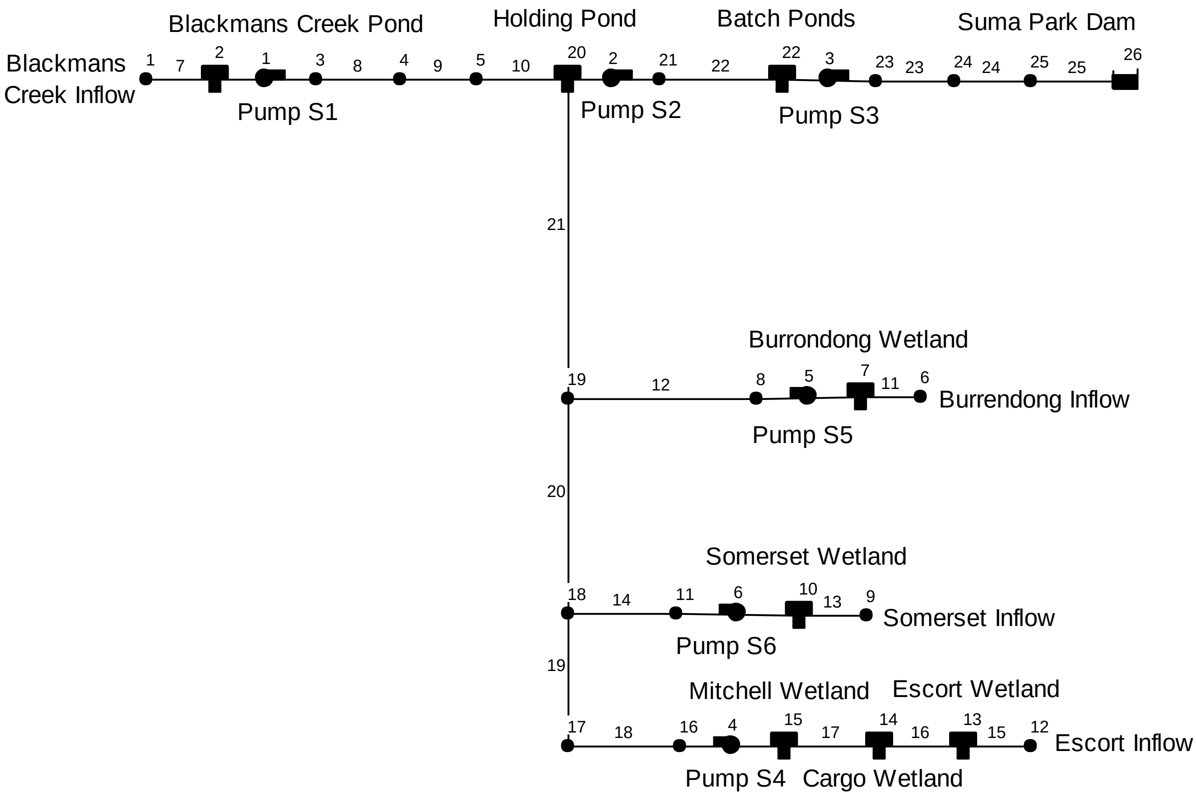

Figure F.4: Schematic of the Stormwater System

Table F.5: Hydraulic Simulation Model Storage Data for the Stormwater System

Node ID	Elevation (m)	Height (m)	Tank Diameter (m)	Capacity (kL)
2 (Blackmans Pond)	832.0	1.0	61.80	3 000
7 (Burrendong Wetland)	826.3	1.0	141.8	15 800
10 (Somerset Wetland)	821.1	1.0	139.6	15 300
13 (Escort Wetland)	921.0	1.0	159.6	20 000
14 (Cargo Wetland)	921.0	1.0	211.1	35 000
15 (Mitchell Wetland)	811.3	1.0	50.00	2 000
20 (Holding Pond)	850.5	7.5	199.7	230 000
22 (Batch Ponds)	854.8	4.6	97.01	34 000
26 (Suma Park Dam)	861.2	-	-	-

Table F.6: Hydraulic Simulation Model Pipe Data for the Stormwater System

Pipe ID	Length (m)	Diameter (mm)	Roughness Height (mm)
8	385	600	0.25
9	279	600	0.25
10	196	600	0.25
12	150	155.6	0.003
14	70	105.2	0.003
18	200	200	0.003
19	200	300	0.25
20	820	300	0.25
21	4887	300	0.25
22	110	301.6	0.003
23	330	317.1	0.25
24	2650	250	0.25
25	556	375	0.25

Note: Pipes 7, 11, 13, 15, 16 and 17 are short, large diameter pipes such that they are essentially frictionless (Length = 1.0 m, Diameter = 1000 mm, Roughness = 0.003 mm).

Table F.7: Pump S1 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	65.0	-
50	61.0	43.2
100	56.3	61.8
150	50.0	69.3
200	42.5	70.1
250	35.8	68.4
300	28.3	61.4
332	20.0	46.5

2 in parallel; single curve given

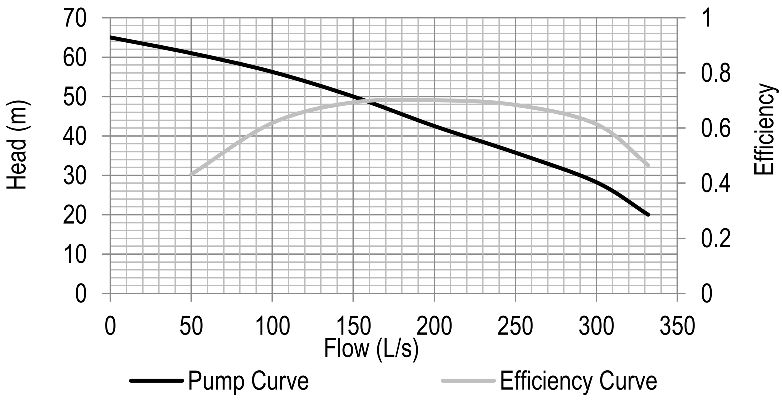

Figure F.5: Pump S1 – Pump and Efficiency Curves

Table F.8: Pump S2 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	38.4	-
20	36.0	50.5
40	29.0	68.1
60	22.5	75.3
80	10.0	46.2

3 in parallel; single curve given

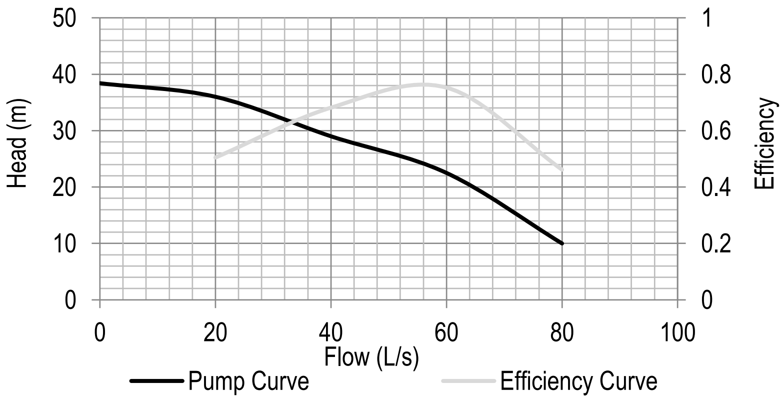

Figure F.6: Pump S2 – Pump and Efficiency Curves

Table F.9: Pump S3 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	93.1	-
20	87.7	50.0
40	76.2	70.0
60	60.0	77.1
79	25.0	46.0

3 in parallel; single curve given

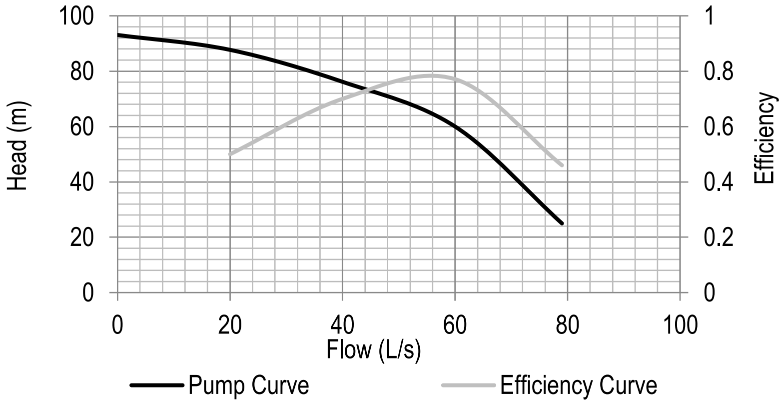

Figure F.7: Pump S3 – Pump and Efficiency Curves

Table F.10: Pump S4 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	83.8	-
10	84.5	49.7
15	83.7	61.7
20	82.2	69.7
25	79.2	74.5
30	76.1	77.1
35	72.0	78.0
40	67.0	77.3
44.93	61.0	74.0

2 in parallel; single curve given

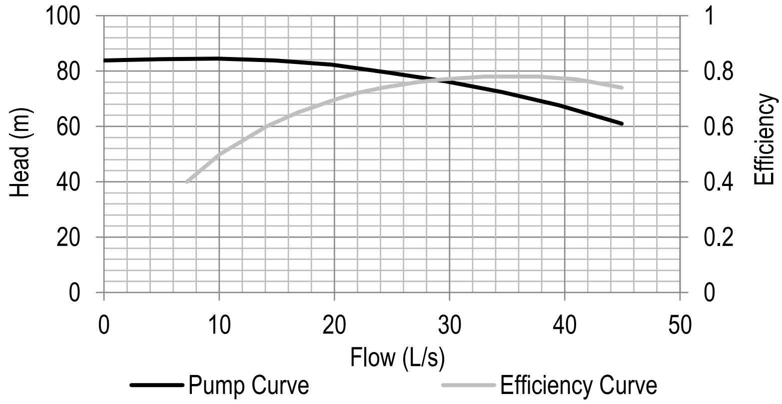

Figure F.8: Pump S4 – Pump and Efficiency Curves

Table F.11: Pump S5 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	68.9	-
1.97	69.4	30.0
2.96	69.1	40.0
3.94	69.0	47.1
4.93	68.1	53.2
5.92	67.2	58.4
6.90	65.9	61.0
7.89	64.3	63.4
8.88	62.4	65.0
9.86	60.4	65.0
10.85	58.1	65.0
12.23	54.3	65.0
13.61	50.5	63.0

2 in parallel; single curve given

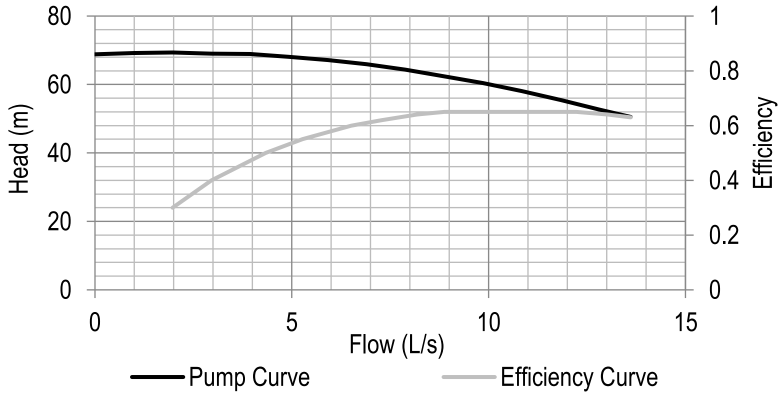

Figure F.9: Pump S5 – Pump and Efficiency Curves

Table F.12: Pump S6 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	98	-
1.67	97	22.5
3.33	93	40.0
5.0	89	52.5
6.67	83	62.5
8.33	76	69.0
10.0	70	72.5
11.67	64	75.0
13.33	57	75.0
15.00	47	73.0
16.67	38	70.0

2 in parallel; single curve given

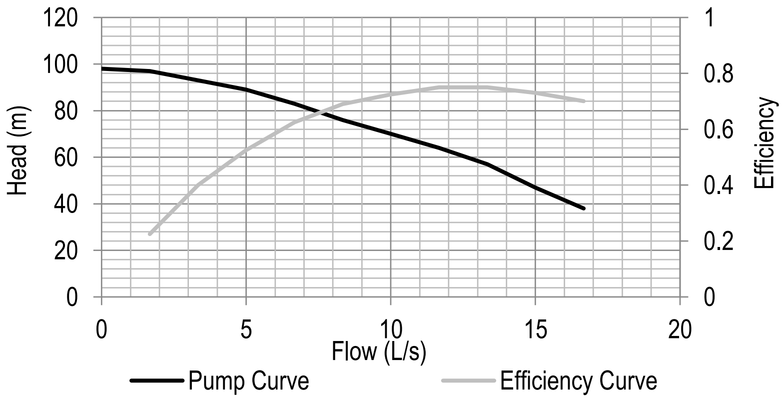

Figure F.10: Pump S6 – Pump and Efficiency Curves

Table F.13: Pump Data at Target Operating Points for the Stormwater System

Pump ID	Total Flow (L/s)	No. of Parallel Pumps	Flow per Pump (L/s)	Head (m)	Efficiency (%)
1	450	2	225	39.1	69.2
2	150	3	50	25.8	71.7
3	150	3	50	68.1	73.6
4	50	2	25	79.2	74.5
5	20	2	10	60.1	65.0
6	20	2	10	70.0	72.5

F3: Imported Water – Macquarie Pipeline

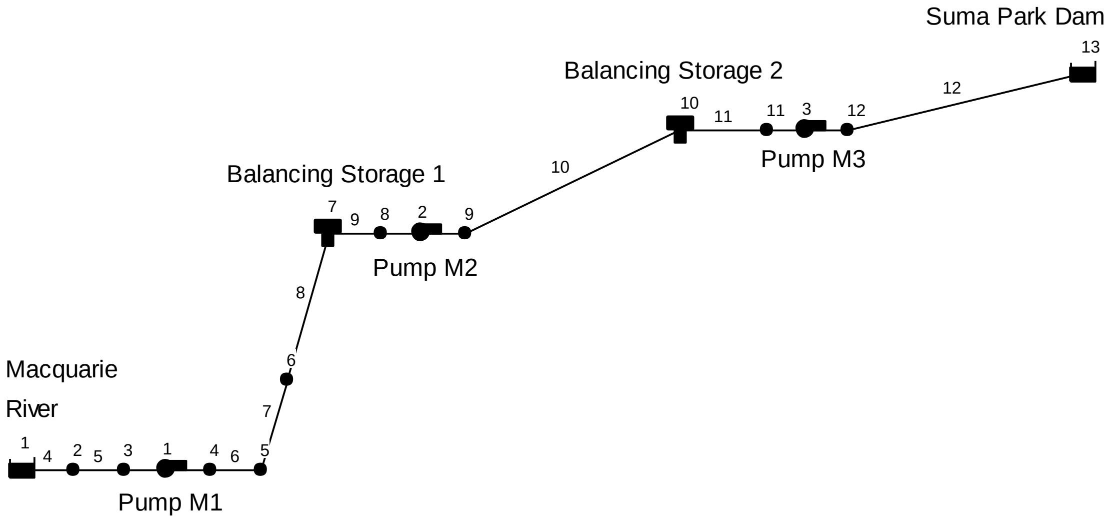

Figure F.11: Schematic Model of the Macquarie Pipeline System

Table F.14: Hydraulic Simulation Model Node Data for the Macquarie Pipeline System

Node ID	Elevation (m)	Height (m)	Diameter (m)	Capacity (kL)
1 (Macquarie River)	370.32	-	-	-
2	370.32	-	-	-
3	370.32	-	-	-
4	370.32	-	-	-
5	370.32	-	-	-
6	510.0	-	-	-
7 (Balancing Storage 1)	649.5	5.09	5.0	100
8	646.0	-	-	-
9	646.0	-	-	-
10 (Balancing Storage 2)	770.76	5.09	5.0	100
11	768.0	-	-	-
12	768.0	-	-	-
13 (Suma Park Dam)	861.2	-	-	-

Table F.15: Hydraulic Simulation Model Pipe Data for Macquarie Pipeline System

Pipe ID	Length (m)	Diameter (mm)	Roughness Height (mm)	Minor Loss Coefficient (k)
4	3	350	0.15	2.90
5	17	550	0.15	1.20
6	5	225	0.15	1.25
7	2622	421	0.15	16.79
8	4541	401	0.15	20.53
9	20	225	0.15	2.7
10	11787	401	0.15	36.56
11	20	225	0.15	2.7
12	19400	401	0.15	49.64

Table F.16: Pump M1 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	404	-
20	388	36.7
40	379	62.5
60	363	75.0
80	329	80.0
90	304	81.0
100	279	80.0
120	213	73.3
136	150	61.7

2 in parallel; single curve given

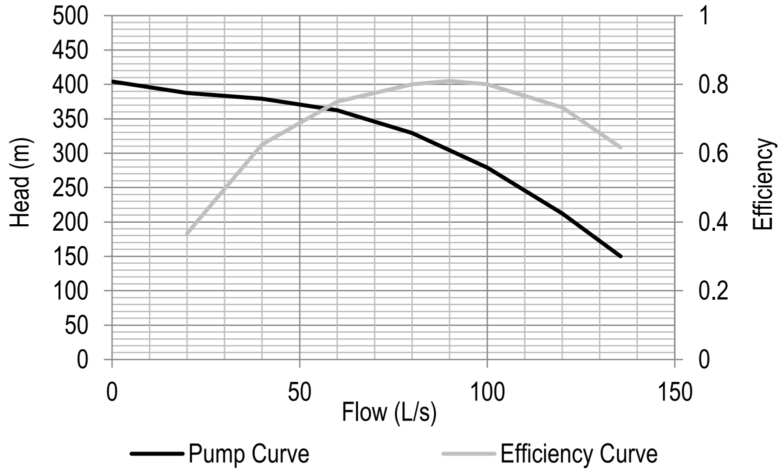

Figure F.12: Pump M1 – Pump and Efficiency Curves

Table F.17: Pumps M2 and M3 – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	254	-
20	243	30.4
40	235	53.6
60	222	67.9
80	204	78.6
93	189	81.0
100	180	78.9
120	143	71.4
135	109	62.5

2 in parallel; single curve given

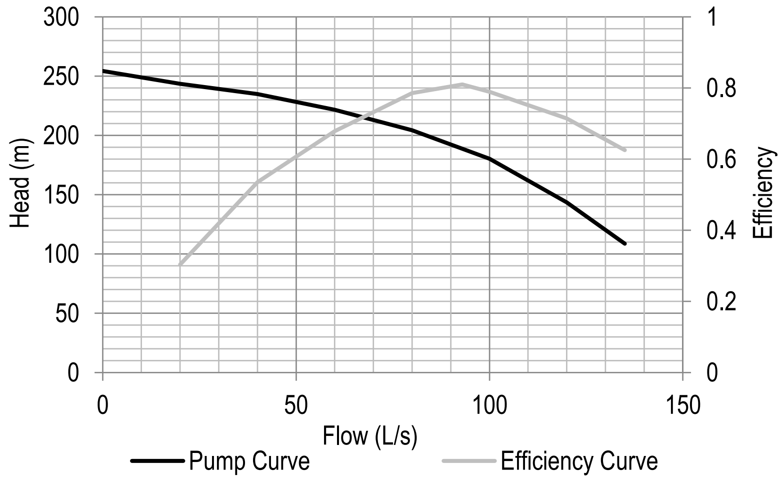

Figure F.13: Pumps M2 and M3 – Pump and Efficiency Curves

Table F.18: Pump Data at Target Operating Points for the Macquarie Pipeline System

Pump ID	Total Flow (L/s)	No. of Parallel Pumps	Flow per Pump (L/s)	Head (m)	Efficiency (%)
1	185	2	92.5	297.9	80.6
2	185	2	92.5	189.4	80.1
3	185	2	92.5	189.4	80.1

F4: Groundwater

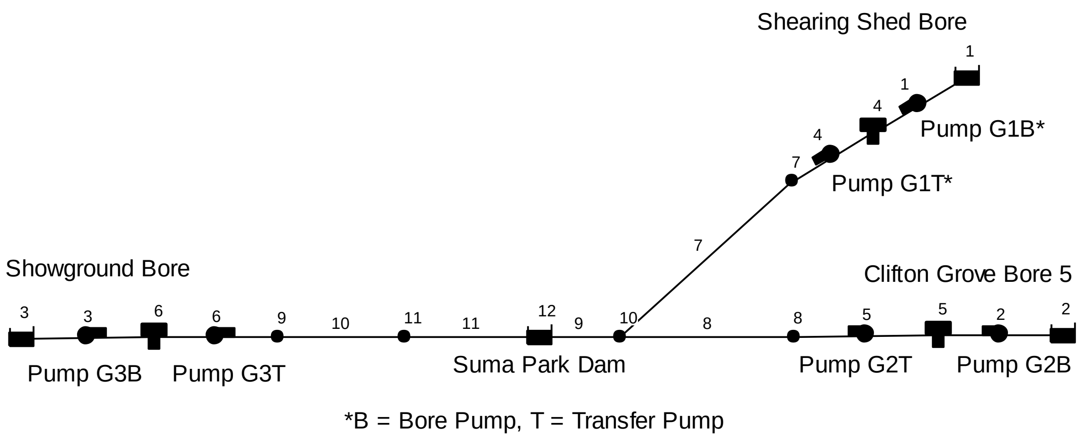

Figure F.14: Schematic of the Groundwater System

Table F.19: Aquifer Data for the Groundwater System

Node ID	Capacity (ML/year)
1 (Shearing Shed Aquifer)	182 (combined with node 2)
2 (Clifton Grove Aquifer)	182 (combined with node 1)
3 (Showground Aquifer)	280

Table F.20: Hydraulic Simulation Model Storage Data for the Groundwater System

Node ID	Elevation (m)	Height (m)	Diameter (m)
4 (Shearing Shed Tank)	855	2.2	291.3
5 (Clifton Grove Tank)	825	2.2	147.1
6 (Showground Tank)	849	2.2	403.3
10 (Suma Park Dam)	861.2	-	-

Table F.21: Hydraulic Simulation Model Pipe Data for Groundwater System

Pipe ID	Length (m)	Diameter (mm)	Roughness Height (mm)
7	3000	101	0.003
8	1000	101	0.003
9	1000	101	0.003
10	1700	101	0.003
11	2400	250	0.25

Each groundwater pumping station has two pumps; a bore pump (designated B) and a transfer pump (designated T), with a storage tank in between.

Table F.22: Pump G1B – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	122	-
1.11	120	15.0
2.78	117	35.0
5.56	108.5	55.0
8.33	99.0	68.0
11.1	88.5	74.0
12.8	77.0	76.0
13.9	70.0	75.0
16.7	47.0	65.0

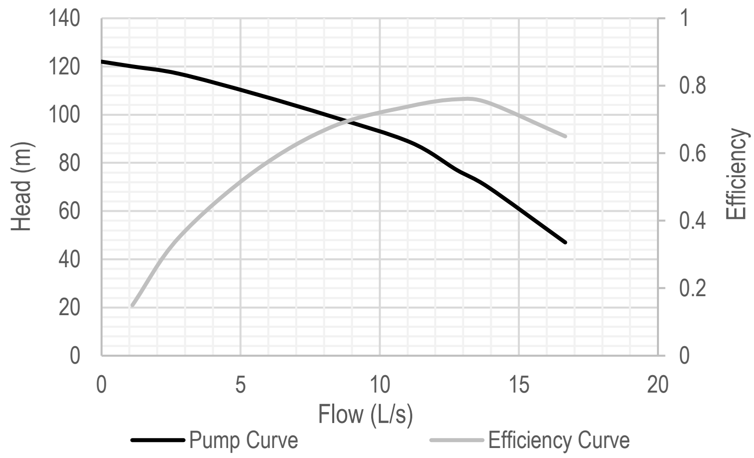

Figure F.15: Pump G1B – Pump and Efficiency Curves

Table F.23: Pump G1T – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	71.5	-
4	67.5	55.0
5	65.5	62.0
6	64.0	68.0
7	62.0	71.0
8	58.5	73.0
9	55.0	73.5
10	50.5	72.0
11.2	45.5	69.0

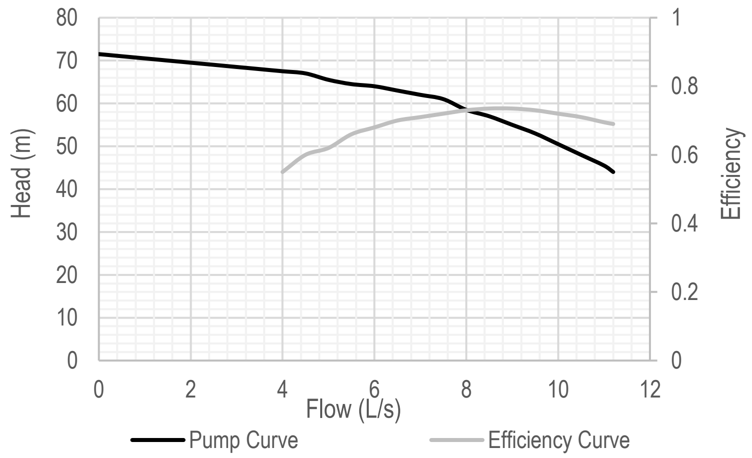

Figure F.16: Pump G1T – Pump and Efficiency Curves

Table F.24: Pump G2B Tabulated Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	78	-
0.56	76.5	24.5
1.11	74.0	40.0
1.67	72.0	52.5
2.22	68.0	60.0
2.78	64.0	65.0
3.33	60.0	69.0
3.89	54.0	71.0
4.44	47.0	70.0
5.00	37.5	66.0

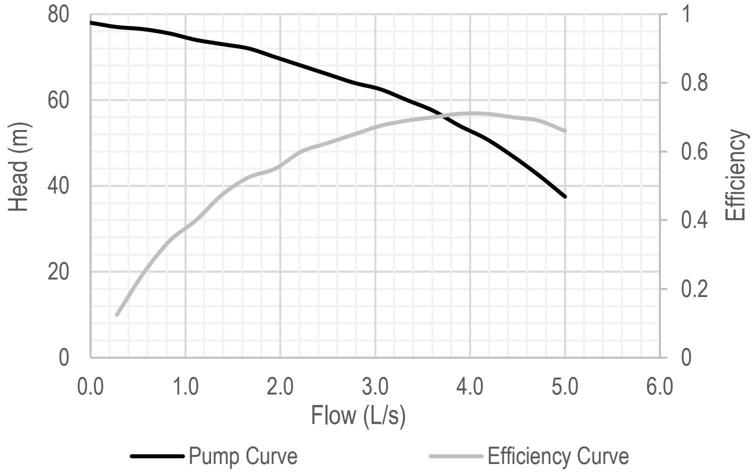

Figure F.17: Pump G2B – Pump and Efficiency Curves

Table F.25: Pump G2T Tabulated Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	43.4	-
2.0	41.0	52.0
2.4	39.7	58.0
2.8	39.0	60.2
3.2	38.0	65.0
3.6	37.0	68.0
4.0	36.5	70.0
4.2	34.2	70.5
4.8	32.5	70.0
5.2	30.5	69.0
5.6	27.8	67.0
6.0	25.5	63.0
6.4	22.5	60.0
6.8	19.5	56.0

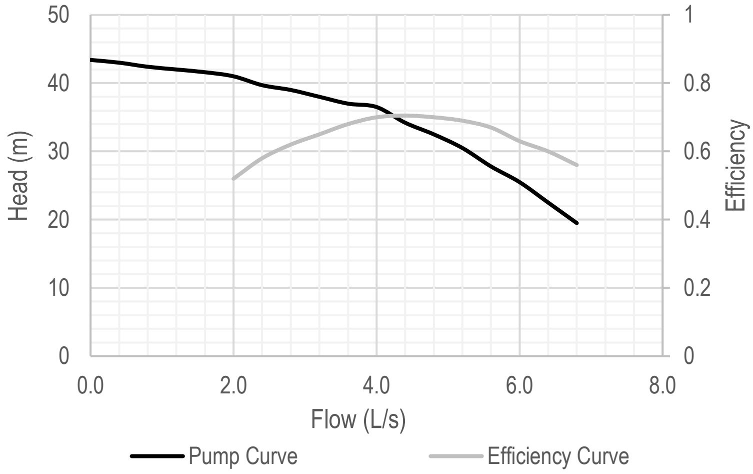

Figure F.18: Pump G2T – Pump and Efficiency Curves

Table F.26: Pump G3B Tabulated Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	118	-
6	115	62.0
7	114	68.0
8	112	71.0
9	110	74.0
10	105	76.0
11	101	77.6
12	96	77.6
13	89	76.0
14	83	74.0
15	75	70.0
16	67	64.0
17	57	58.0

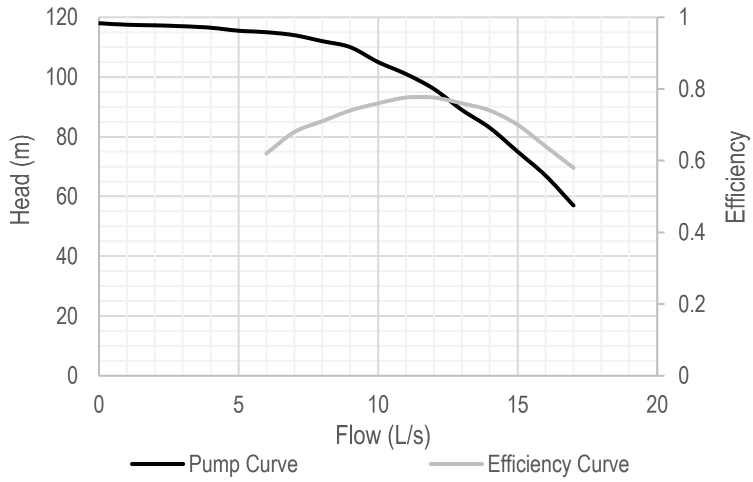

Figure F.19: Pump G3B – Pump and Efficiency Curves

Table F.27: Pump G3T – Pump and Efficiency Curves

Flow (L/s)	Head (m)	Eff. (%)
0	54	-
2.78	52	30.0
5.56	48	55.0
8.33	42	68.0
11.1	37	75.0
13.9	30	75.0
16.7	20	60.0

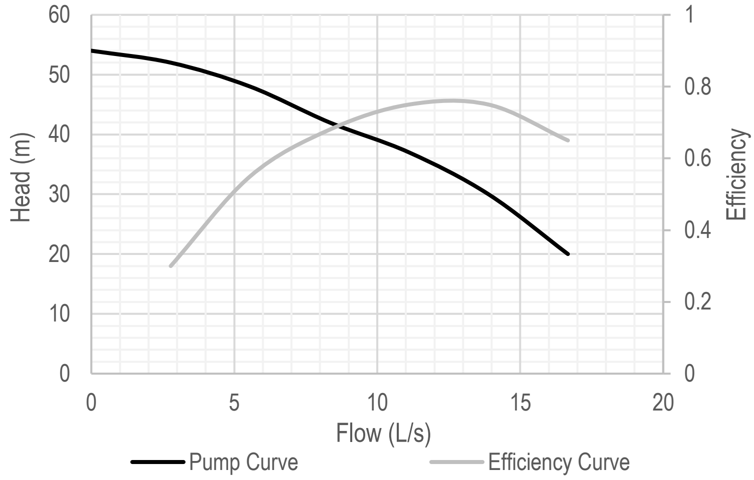

Figure F.20: Pump G3T – Pump and Efficiency Curves

Table F.28: Pump Data at Target Operating Points for the Groundwater System

Pump ID	Flow (L/s)	Head (m)	Efficiency (%)
1 (G1B)	10	92.7	71.6
4 (G1T)	10	50.5	72.0
2 (G2B)	2.5	66.0	62.5
5 (G2T)	2.5	39.5	59.0
3 (G3B)	12.5	92.5	76.8
6 (G3T)	12.5	33.5	75.0

F5: Other Data

Table F.29: Summary of Rainfall, Runoff and Demand Data Available

Location	Organisation	Start Date	End Date	Data Type
Orange, New South Wales	Orange City Council, New South Wales, Australia	1/1/1890	31/12/2007	Daily rainfall on Spring Creek and Suma Park
Orange, New South Wales	Orange City Council, New South Wales, Australia	1/1/1890	31/12/2007	MUSIC generated daily runoff for stormwater and surface water catchments
Orange, New South Wales	Orange City Council, New South Wales Australia	1/1/1890	31/12/2007	Predicted daily demand from Suma Park

Table F.30: Electricity Tariff Data – Stormwater and Groundwater Systems

Tariff	Times	Energy Cost (c/kWh)
Peak	7am – 9am, 5pm – 8pm Weekdays	12.3964
Shoulder	9am – 5pm, 8pm – 10pm Weekdays	12.3964
Off-peak	12am – 7am, 10pm – 12pm Weekdays and all Weekend	6.1664

Table F.31: Electricity Tariff Data – Macquarie Pipeline System

Tariff	Times	Energy Cost (c/kWh)	Peak Demand Cost ($/kVA)
Peak	7am – 9am, 5pm – 8pm Weekdays	4.4928	8.1296
Shoulder	9am – 5pm, 8pm – 10pm Weekdays	4.4928	8.1296
Off-peak	12am – 7am, 10pm – 12pm Weekdays and all Weekend	2.8655	1.8581

An additional ‘market charge’ of 1.17 c/kWh applies to all systems