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Journal of Water Resources Planning and Management, 2016; 142(6):04016010-1-04016010-11

Published at: http://dx.doi.org/10.1061/(ASCE)WR.1943-5452.0000633

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Journal of Water Resources Planning and Management

Citation: Blinco, L.J., Simpson, A.R., Lambert, M.F., and Marchi, A. (2016). "Comparison of Pumping Regimes for Water Distribution Systems to Minimize Cost and Greenhouse Gases." *Journal of Water Resources Planning and Mangement*, 142(6), doi: 10.1061/(ASCE)WR.1943-5452.0000633.

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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[2], Martin F. Lambert[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 EPANET 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 to its current operation.

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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 new programmer's toolkit for EPANET hydraulic simulation software (called "EPANET2-ETTAR" – EPANET2 Toolkit to Alter Rules) has been developed by Marchi and Simpson (2015). This toolkit has been used to allow the optimization model to alter rule-based controls in EPANET, which therefore has allowed more complex pump operating regimes to be considered. Human-induced climate change presents a serious global risk and action to mitigate our impact by reducing GHG emissions is important. Production of electrical energy for WDS pumping operations is the biggest contributor to GHG emissions from the water industry (Stokes and Horvath 2005; Wu et al. 2013).

This paper describes the development of a single-objective genetic algorithm (GA) optimization model for WDS pump operations integrating EPANET (including EPANET2-ETTAR) and an 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 EPANET (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 & Awumah 1994); system effectiveness (Carravetta et al. 2013a), resilience (Prasad & 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 the current 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, 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. Multi-objective optimization of cost and GHG emissions for WDSs has been extensively covered in Wu et al. (2010a); Wu et al.

(2010b); Wu et al. (2011); Stokes et al. (2012b); Stokes et al. (2012c); Wu et al. (2012a); Wu et al. (2012b); Wu et al, (2013); and Stokes et al. (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 (for example, in 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, 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/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, as 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), Wu et al. (2010a) and Wu et al. (2010b). 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.

Genetic Algorithms (GAs) represent an efficient method for the optimization of non-linear 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 an 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 bit wise 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 1:

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

where OC = operational cost in $/m^3, T_i = electricity tariff in $/kWh and E_i = energy consumption in kWh for each time step i, and V = total volume pumped in 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 multi-part 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 EPANET, 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 between 7am and 11pm and an off-peak electricity price of 9 c/kWh from 11pm to 7am.

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:

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

where OGHG = operational GHG emissions in kg CO_2-eq/m^3, F_i = emissions factor in kg CO_2-eq/kWh and E_i = energy in kWh at each time step i, which ranged from 0 to 23 for hourly time increments. Emission factor data was collated from Dey and Lenzen (2006), 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.

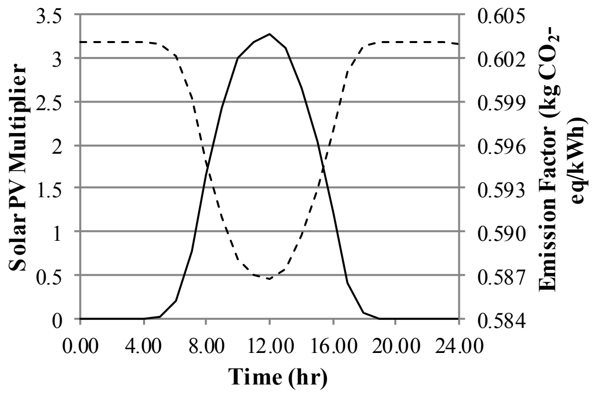


Fig. 1. Daily variation in solar photovoltaic output (solid) and emission factors (dashed)

A number of constraints could be used in the optimization process, with penalties added to the objective function in the case of constraint violation. As well as pressure, velocity and headloss 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 hour 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: (A) lower and upper trigger levels (B) a reduced upper trigger level (C) combined trigger levels and scheduling (D) variable trigger levels and (E) variable speed pump scheduling. The pump operation was optimized over a period of 24 hours, 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 ending water level of the tank is likely to be close to the beginning 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.

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, 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, as 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 with 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-hour 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, as 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.

Variable speed pumps (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): (i) 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 (ii) the shut off 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. Note that 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 to hourly time intervals with only 24 decision variables. For systems with multiple pumps, a larger time interval may need to be used as 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: A One-Pipe Network

The models were initially used to analyze a one-pipe network introduced by Wu et al. (2010a), who performed a multi-objective optimization for the pump size and pipe diameter of the network, finding eight non-dominated 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 m 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 shut off head of the pump is equal to the static head of the system. At full speed (1475 rpm), the pump shut off 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 conservative, a minimum value of 0.85 is considered (equivalent to approximately 1254 rpm).

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

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

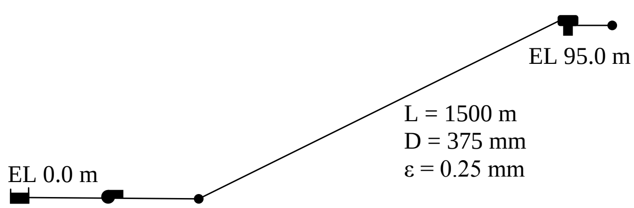


Fig. 2. One-pipe network

Table 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

Control Case A: Cost Minimization

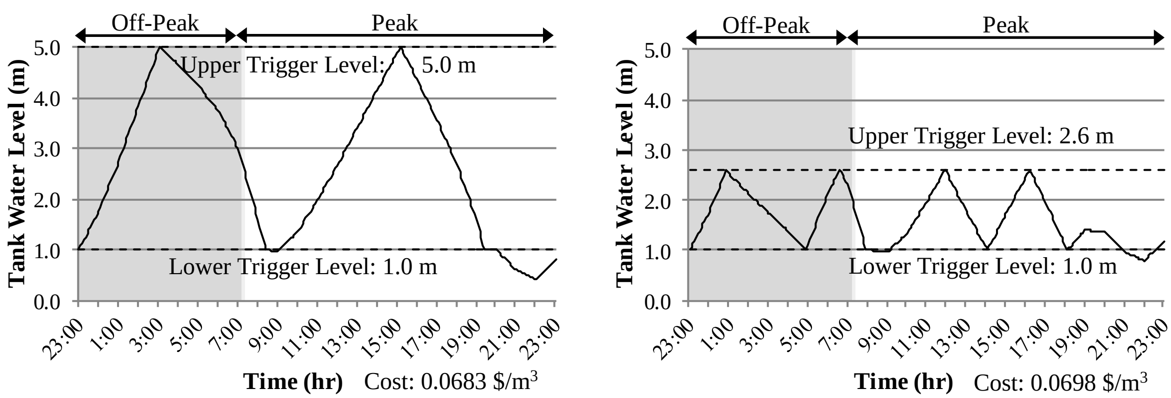
When optimizing pump operating Control Case A, a lower trigger level of 1.0 m and an upper trigger level of 5.0 m was the best solution in terms of cost (Table 3). As there were only two decision variables, each with 21 possible values (using increments of 0.2 m), the total number of possible solutions 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 seven, eight and ten 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 (Columns 3 to 5 of Table 3). 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 in Column 6, 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 to the first six solutions (Columns 7 and 8). 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 3. Top solutions from pump operating Control Case A optimization for the one-pipe network

Solution	Cost ($\$/m^3$)	Lower Trigger Level (m)	Upper Trigger Level (m)	Trigger Level Range (m)	Energy (kWh/m^3)	Peak Energy (%)	Off-peak Energy (%)	Min. Water Level (m)[a]	GHGs (kg CO_2-eq/m^3)
1	2	3	4	5	6	7	8	9	10
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] the maximum tank level for each solution is equal to the upper trigger level (column 4)

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 (Column 9 of Table 3). If a minimum tank level constraint of 1 m is used, the optimal trigger levels are found to be 1.6 m and 3.2 m (the tenth 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 m 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.



(a) Control Case A – 1st Solution (b) Control Case A – 7th Solution

Fig. 3. Daily tank level variation of the one-pipe network: cost optimization (a) pump operating Control Case A – 1st Solution and (b) Control Case A – 7th Solution

Control Case A: GHG Minimization

The optimal solution for GHG emissions was different to the optimal cost solution. The lower and upper trigger levels were as low and as close together as possible, at 1.0 m 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 ten cost solutions (Column 10 of Table 3). As 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 to the \$0.0683/m^3 for the Control Case A solution. A switch time of 2am gave the lowest cost and was able to fill the tank just before the start of the peak period at 7am (Fig. 4a). Using a reduced upper trigger level did not benefit GHG emissions as 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.

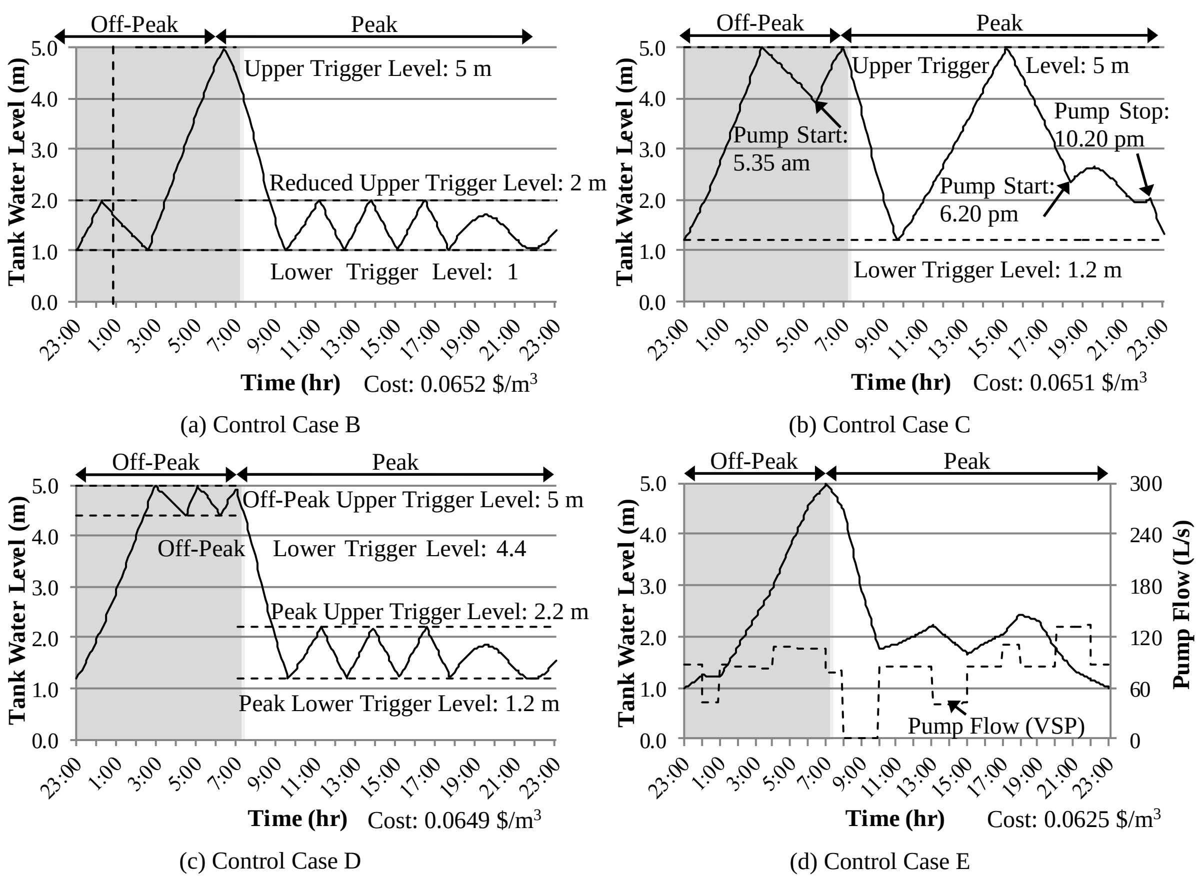


Fig. 4. Daily tank level variation of the one-pipe network: cost optimal solution for (a) pump operating Control Case B, (b) Control Case C, (c) Control Case D and (d) Control Case E

Control Case C: Cost Minimization

For Control Case C, the combination of trigger levels and scheduling, the cost was reduced slightly compared to 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 start up during the peak time was considered as well as those proposed in the methodology. The time range for this pump start-up was 4pm to 10pm at an increment of 5 minutes, which allowed the tank level to stay above 1 m, and a pump shut off was considered between 10pm and 11.30pm, also at an increment of 5 minutes. The optimal cost solution found using this strategy again had wide trigger levels of 1 m and 5 m, the pump was started again at 5.35am and this allowed the tank to fill exactly for the start of the peak period (Fig. 4b). During the peak period, the optimal solution started the pump at 6.20pm and then shut it down at 10.20pm 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 m and 2.2 m, and a high water level during the off-peak period, with trigger levels of 4.4 m and 5.0 m (Fig. 4c). Even though this solution had a slightly greater percentage of pumping during the peak period compared to 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 to the other control cases. The best cost solution using variable speed pumps (VSPs) used lower pump speeds throughout the off-peak period to fill the tank exactly at the start of the peak period (Fig. 4d) and had a cost of \$0.0625/m^3. The use of fixed speed pumps (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 to 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 kg CO_2-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 to the pump operational flow of 126 L/s, the pump in this network was oversized and only required to operate for eight hours each day. Under the current operational regime using trigger levels of 3.96 m and 5.54 m, almost half of this pumping occurred during the peak electricity tariff period (Fig. 6), when electricity rates were much higher (22c/kWh compared to 9c/kWh for off-peak). Cost and GHG emissions for the current operation were \$0.0360/m^3 and 0.1460 kg CO_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 m 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 with a pump shut off 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.

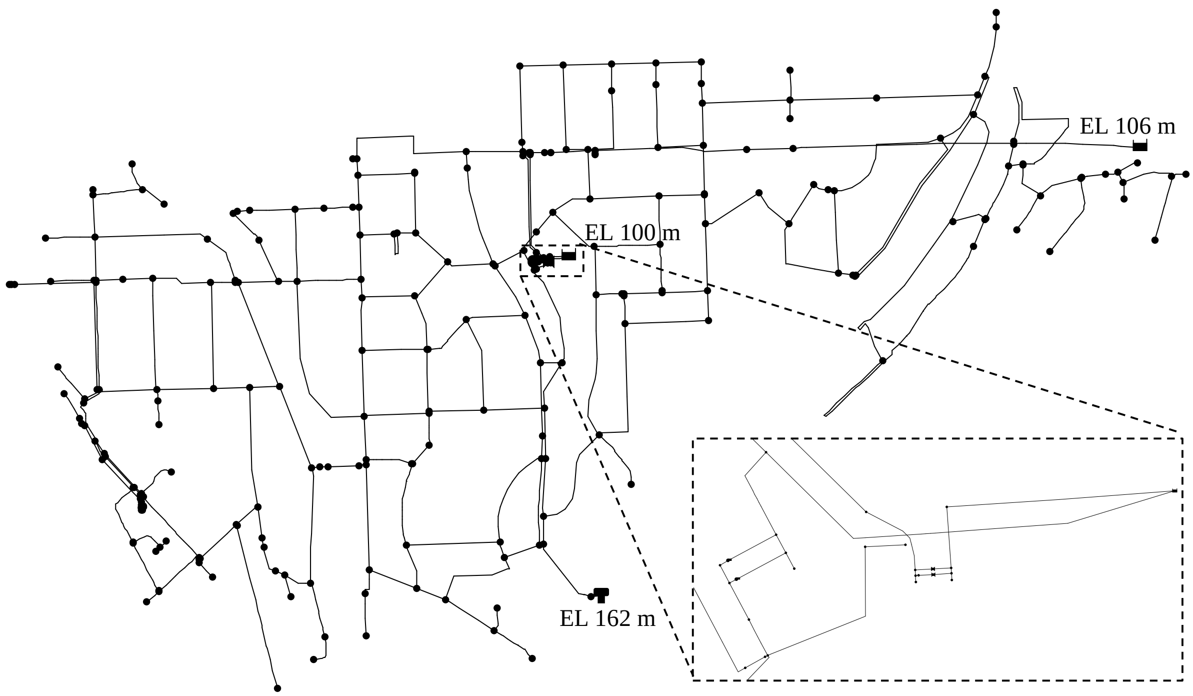


Fig. 5. South Australian network

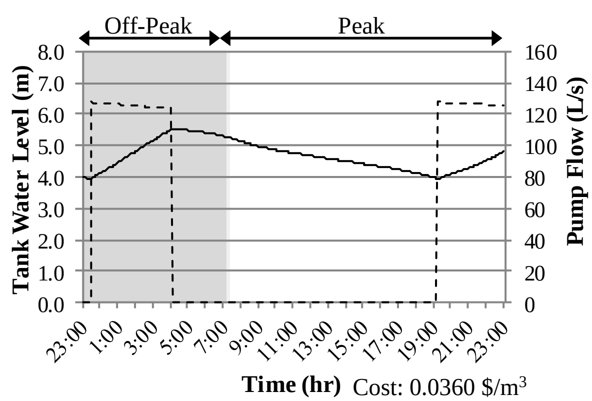


Fig. 6. Daily tank level (solid) and pump flow (dashed) variation for the South Australian network: current operation

Table 4. Optimal solutions for each pump operating control case for the South Australian network

Control Case	Objective	Cost ($/m^3)	Cost 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/GHG in the optimal solution is less than the current operation (cost: $0.0360/m^3, GHG: 0.1460 kg CO_2-eq/m^3)

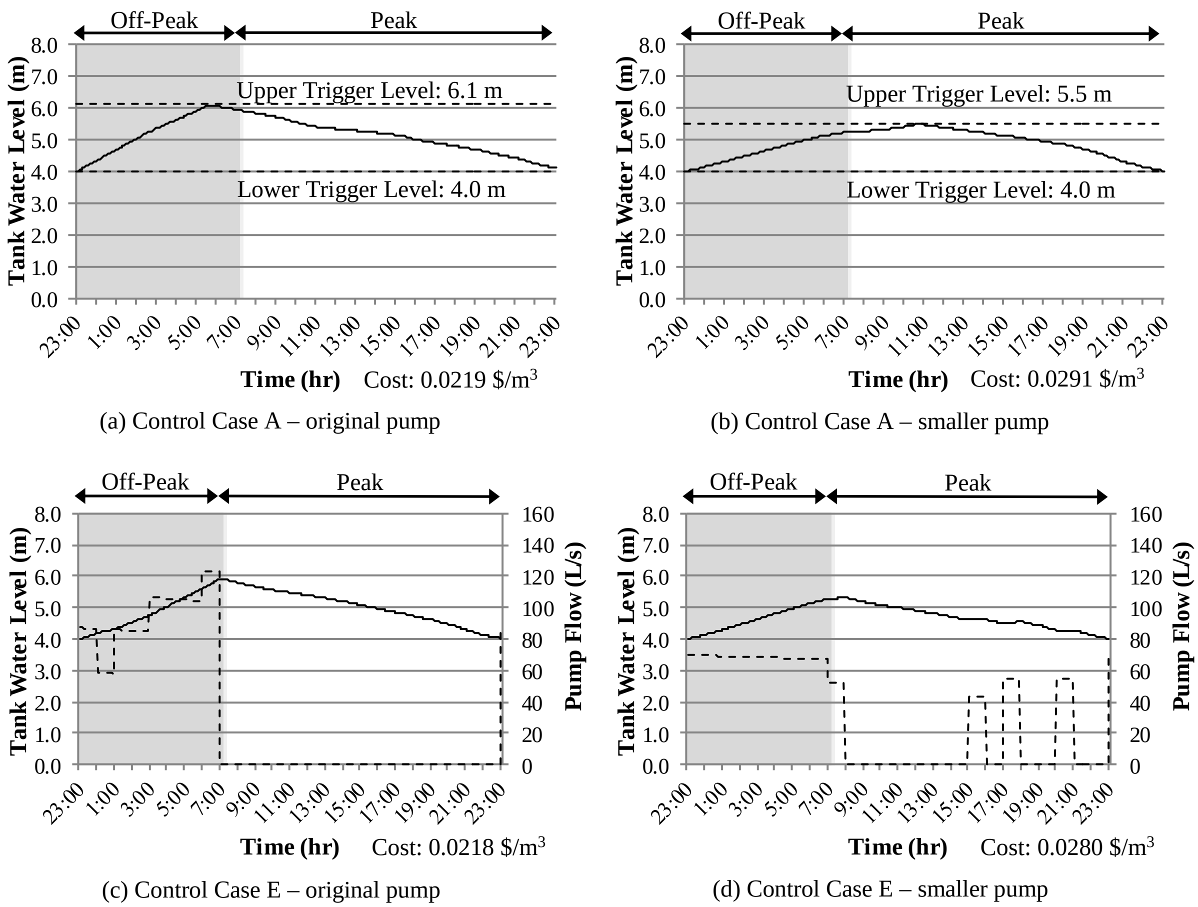
Table 5. Optimal solutions for each pump operating control case for the South Australian network with a smaller pump

Control Case	Objective	Cost ($/m^3)	Cost 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/GHG 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)

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 11pm and 6.30am and then draining for the rest of the day (Fig 7a). 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).



(a) Control Case A – original pump

(b) Control Case A – smaller pump

(c) Control Case E – original pump

(d) Control Case E – smaller pump

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 and (d) Control Case E with smaller pump

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 11pm to 6am and then at full speed for the last hour of the off-peak period (Fig. 7c). While the reduced speed would lead to less friction loss through the system and hence reduced energy requirements, there was an extra 90 minutes 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 to 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 eight off-peak hours each day. The current pump operated at a flow of 126 L/s at a head of around 70 m. As the average demand was 30.7 L/s, a pump with a flow of around 40 L/s at a head of 70 m was selected. This pump required roughly 13 hours of pumping per day. The shut off 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 m 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 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. 7b). This solution still reduced the cost by 19% compared to 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 to the current operation. With the smaller pump, however, the cost optimal trigger levels also reduced GHG emissions by around 8%. The optimal GHG trigger levels when the smaller pump was used were 4.0 m 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 start up 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, as some pumping in the peak period was required (Fig. 7d). The optimal GHG pump schedule with the smaller pump provided the best GHG solution for all of the South Australian network solutions in Table 4 and 5 with emissions of 0.1315 kg CO_2-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 EPANET which 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 to 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/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) as 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, as all pumping could be achieved in the off-peak period. Using a smaller pump was more expensive, as some peak pumping was required, however, was able to reduce GHG emissions at the same time as reducing cost compared to 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 to the current operation of the South Australian network.

Acknowledgements

The support of the Commonwealth of Australia through the Cooperative Research Centre program is acknowledged. This research was part of the CRC for Water Sensitive Cities Project C5.1 (Intelligent Urban Water Networks) and was supported by funding for post-doctoral research and a PhD top-up scholarship. The authors would like to thank X.J. Wang at SA Water for providing information to allow the model to be applied to a real-life network.

References

Australian Energy Market Operator. (2011). "2011 South Australian supply and demand outlook." Melbourne, Victoria.

Basupi, I., and Kapelan, Z. (2015). "Felxible water distribution system design under future demand uncertainty." Journal of Water Resources Planning and Management, 141.

Boulos, P., Wu, Z. Y., Orr, C., Moore, M., Hsiung, P., and Thomas, D. (2001). "Optimal pump operation of water distribution systems using genetic algorithms." AWWA Distribution System Symposium, American Water Works Association, Denver, Colorado, USA.

Carravetta, A., Del Giudice, G., Fecarotta, O., and Ramos, H. M. (2013a). "Pump as turbine (PAT) design in water distribution network by system effectiveness." Water, 5, 1211-1225.

Carravetta, A., Fecarotta, O., Martino, R., and Antipodi, L. "PAT efficiency variation with design parameters." 12th International Conference on Computing and Control for the Water Industry, CCWI2013, Perugia, Italy, 285-291.

Dandy, G. C., Roberts, A., Hewitson, C., and Chrystie, P. (2006). "Sustainability objectives for the optimization of water distribution networks." 8th Annual Water Distribution Systems Analysis Symposium, American Society of Civil Engineers, Cincinnati, Ohio, USA.

Dey, C., and Lenzen, M. (2006). "Greenhouse gas analysis of electricity generation systems." *Renewable Energy Transforming Business*, 658-668.

Evans, A., Sterzov, V., and Evans, T. (2010). "Comparing the sustainability parameters of renewable, nuclear and fossil fuel electricity generation technologies." World Energy Congress, Montreal, Canada.

Fecarotta, O., Aricó, C., Carravetta, A., Martino, R., and Ramos, H. M. (2015). "Hydropower potential in water distribution networks pressure control by PATs." Water Resources Management, 29, 699-714.

Giustolisi, O., Berardi, L., Laucelli, D., Savic, D., and Kapelan, Z. (2015). "Operational and tactical management of water and energy resources in pressurized systems: competition at WDSA 2014." Journal of Water Resources Planning and Management, Published online 27 Aug 2015.

Giustolisi, O., Laucelli, D., and Berardi, L. (2013). "Operational optimization: water losses versus energy cost." Journal of Hydraulic Engineering, 139(4).

Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*, Addison-Wesley, Reading, Massachusetts.

Goldberg, D. E. (1994). "Genetic and evolutionary algorithms come of age." *Communications of the ACM*, 37(3), 113-119.

Goryashko, A. P., and Nemirovski, A. S. (2014). "Robust energy cost optimization of water distribution system with uncertain demand." Automation and Remote Control, 75(10), 1754-1769.

Kazantzis, M., Simpson, A. R., Kwong, D., and Tan, S. M. (2002). "A new methodology for optimizing the daily operations of a pumping plant." Conference on Water Resources Planning and Management, American Society of Civil Engineers, Virginia, USA.

Lansey, K. E., and Awumah, K. (1994). "Optimal pump oeprations considering pump switches." Journal of Water Resources Planning and Management, 120(1), 17-35.

Lenzen, M. (2008). "Life cycle energy and greenhouse gas emissions of nuclear energy: A review." *Energy Conversion and Management*, 49, 2178-2199.

López-Ibáñez, M., Prasad, T. D., and Paechter, B. (2005). "Multi-objective optimisation of pump scheduling problem using SPEA2." IEEE Congress on Evolutionary Computing, Institute of Electrical and Electronics Engineers, Edinburgh, UK, 435-442.

Mackle, G., Savic, D., and Walters, G. (1995). "Application of genetic algorithms to pump scheduling for water supply." GALESIA 1995, Institute of Electrical Engineers, 400-405.

Marchi, A., and Simpson, A. (2015). "New possibilities for the optimization of pump operation using rule-based controls in EPANET2." submitted to the *Journal of Water Resources Planning and Management*.

Marchi, A., Simpson, A. R., and Ertugrul, N. (2012). "Assessing variable speed pump efficiency in water distribution systems." Drinking Water Engineering and Science, 5, 1-19.

Morley, M. S., Tricarico, C., and de Marinis, G. "Multiple-objective evolutionary algorithm approach to water distribution system model design." 14th Water Distribution Systems Analysis Conference, Adelaide, Australia, 551-559.

Paschke, M., Spencer, K., Waniarcha, N., Simpson, A., and Widdop, T. (2001). "Genetic algorithms for optimisation of pumping operations." Australian Water Association 19th Federal Convention, Canberra.

Prasad, T. D., and Park, N.-S. (2003). "Multiobjective genetic algorithms for design of water distribution networks." Journal of Water Resources Planning and Management, 130, 73-82.

Simpson, A. R. (2009). "How to account for sustainability in the design and operation of water distribution systems." World City Water Forum, Incheon, Korea, 279-286.

Simpson, A. R., Dandy, G. C., and Murphy, L. J. (1994). "Genetic algorithms compared to other techniques for pipe optimisation." *Journal of Water Resources Planning and Management*, 120(4), 423-443.

Stokes, C., Simpson, A. R., and Maier, H. R. (2014). "The cost-greenhouse gas emission nexus for water distribution systems including the consideration of energy generating infrastructure: an integrated conceptual optimization framework and review of literature." Earth Perspectives, 1(9).

Stokes, C., Wu, W., and Dandy, G. C. (2012a). "Battle of the water networks II: combining engineering judgement with genetic algorithm optimisation." 14th Water Distribution Systems Analysis Conference, American Society of Civil Engineers, Adelaide, Australia.

Stokes, C. S., Maier, H. R., and Simpson, A. R. (2012b). "Water distribution system greenhouse gas emission reduction by considering the use of time-dependent emissions factors." 14th Water Distribution Systems Analysis Conference, American Society of Civil Engineers, Adelaide, Australia.

Stokes, C. S., Simpson, A. R., and Maier, H. R. (2012c). "An improved framework for the modelling and optimisation of greenhouse gas emissions associated with water distribution systems." International Congress on Environmental Modelling and Software, Leipzig, Germany.

Stokes, J., and Horvath, A. (2005). "Life cycle energy assessment of alternative water supply systems." *International Journal of Life Cycle Assessment*, 1-9.

Walski, T., Zimmerman, K., Dudinyak, M., and Dileepkumar, P. "Some surprises in estimating the efficiency of variable speed pumps with the pump affinity laws." World *Water and Environmental Resources Congress 2003*, Philadelphia, PA, 1-10.

Wang, Q., Guidolin, M., Savic, D., and Kapelan, Z. (2015). "Two-objective design of benchmark problems of a water distribution system via MOEAs: towards the best-known approximation of the true Pareto front." Journal of Water Resources Planning and Management, 141(3).

Wu, W., Maier, H. R., and Simpson, A. R. (2010a). "Single-objective versus multiobjective optimization of water distribution systems accounting for greenhouse gas emissions by carbon pricing." *Journal of Water Resources Planning and Management*, 136(5), 555-565.

Wu, W., Maier, H. R., and Simpson, A. R. (2013). "Multiobjective optimization of water distribution systems accounting for economic cost, hydraulic reliability, and greenhouse gas emissions." *Water Resources Research*, 49, 1211-1225.

Wu, W., Simpson, A. R., and Maier, H. R. (2010b). "Accounting for greenhouse gas emissions in multiobjective genetic algorithm optimization of water distribution systems." *Journal of Water Resources Planning and Management*, 136(2), 146-155.

Wu, W., Simpson, A. R., and Maier, H. R. (2011). "Reducing greenhouse gas emissions from water distribution systems using multi-objective optimisation and variable speed pumping." OzWater'11, Australian Water Association, Adelaide, South Australia.

Wu, W., Simpson, A. R., and Maier, H. R. (2012a). "Sensitivity of optimal tradeoffs between cost and greenhouse gas emissions for water distribution systems to electricity tariff and generation." Journal of Water Resources Planning and Management, 138, 182-186.

Wu, W., Simpson, A. R., Maier, H. R., and Marchi, A. (2012b). "Incorporating variable-speed pumping in multi-objective genetic algorithm optimization of water distribution systems to reduce greenhouse gas emissions." Journal of Water Resources Planning and Management, 138(5), 543-552.