Available online at www.sciencedirect.com
ScienceDirect
Procedia Engineering 89 (2014) 509 – 516
Procedia Engineering
www.elsevier.com/locate/procedia

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

Peer-review under responsibility of the Organizing Committee of WDSA 2014
doi:10.1016/j.proeng.2014.11.246

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)).

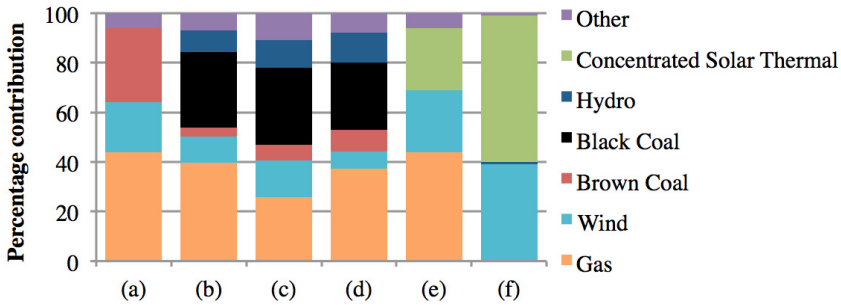

Fig. 1. Energy source scenarios (a) current South Australian (b) AEMO – fast rate of change (c) AEMO – oil shock and adaption (d) AEMO – slow rate of change (e) concentrated solar thermal at Port Augusta and (f) Australia 100% renewable. 'Other' includes oil, geothermal, biomass and solar photovoltaic.

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.

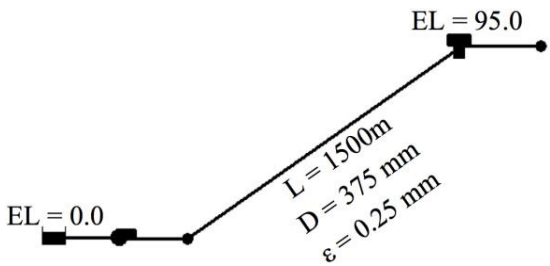

Fig. 2. The one-pipe and one-pump network

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.

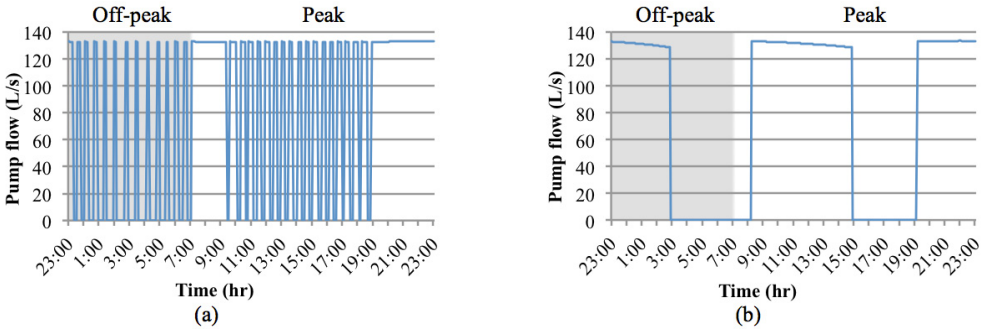

Fig. 3. Daily pump flow variation with trigger levels of (a) 1.0 m and 1.2 m and (b) 1.0 m and 4.8 m

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.

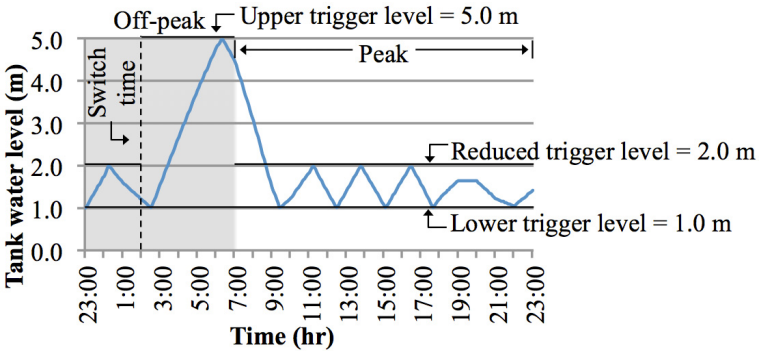

Fig. 4. Daily tank level variation for the optimal cost solution with a reduced upper trigger level

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.

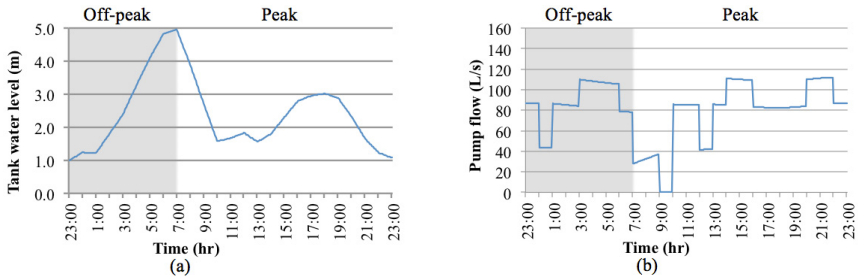

Fig. 5. (a) Daily tank level variation and (b) daily pump flow variation for optimal one-pipe network operation

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

This research was supported by the Cooperative Research Centre for Water Sensitive Cities.

References

[1] P.F. Boulos, Z. Wu, C.H. Orr, M. Moore, P. Hsuing, D. Thomas, Optimal pump operation of water distribution systems using genetic algorithms, American Water Works Association Distribution System Symposium, Denver, Colorado 2001.
[2] W. Wu, H.R. Maier, A.R. Simpson, Single-objective versus multiobjective optimization of water distribution systems accounting for greenhouse gas emissions by carbon pricing, J. Water Resour. Plann. Manage. 136 (2010) 555-565.
[3] A.R. Simpson, Z.Y. Wu, Optimal rehabilitation of water distribution systems using a messy genetic algorithm, Australian Water and Wastewater Association 17th Federal Convention, Melbourne, Victoria 1997.
[4] A.R. Simpson, G.C. Dandy, L.J. Murphy, Genetic algorithms compared to other techniques for pipe optimization, J. Water Resour. Plann. Manage. 120 (1994) 423-443.
[5] M.D. Kazantzis, A.R. Simpson, D. Kwong, S.M. Tan, A new methodology for optimizing the daily operations of a pumping plant, American Society of Civil Engineers Conference on Water Resources Planning and Management, Roanoke, Virginia 2002.
[6] G. Dandy, A. Roberts, C. Hewitson, P. Chrystie, Sustainability objectives for the optimization of water distribution networks, American Society of Civil Engineers 8th Annual Water Distribution Systems Analysis Symposium, Cincinnati, Ohio 2006.
[7] W. Wu, A.R. Simpson, H.R. Maier, Accounting for greenhouse gas emissions in multiobjective genetic algorithm optimization of water distribution systems, J. Water Resour. Plann. Manage. 136 (2010) 146-155.
[8] Australian Energy Market Operator (AEMO), South Australian supply and demand outlook, AEMO 2011, Melbourne, Victoria.
[9] AEMO, National transmission network development plan, AEMO 2010, Melbourne, Victoria.
[10] Beyond Zero Emissions (BZE), Repowering Port Augusta, BZE 2012, Fitzroy, Victoria.
[11] M. Wright, P. Hearps, Zero carbon Australia stationary energy plan, BZE 2010, Fitzroy, Victoria.
[12] D. Keall, The book of Agar, The University of Adelaide 2012, Adelaide, South Australia.
[13] V. Sankey, EAWDNSolverKL user guide, The University of Adelaide 2012, Adelaide, South Australia.