Wu, Wenyan; Simpson, Angus Ross; Maier, Holger R.
Accounting for greenhouse gas emissions in multiobjective genetic algorithm optimization of water distribution systems Journal of Water Resources Planning and Management, 2010; 136(2):146-155

Accounting for Greenhouse Gas Emissions in Multi-Objective Genetic Algorithm Optimization of Water Distribution Systems

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

Keywords: Water distribution systems; Multi-objective optimization; Genetic algorithms; Sustainability; Discounting; Greenhouse gas emissions

Introduction

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

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

While reference to multi-objective optimization has appeared in the literature since late 1960s (Schaake and Lai 1969), in engineering applications, sustainability related issues, such as energy usage (Sarbu and Borza 1998), social cost (Dandy and Hewitson 2000), water quality (Dandy and Hewitson 2000) and material usage (Dandy et al. 2006) have only been introduced into the optimization of WDSs over the last 10 years or so. In the study carried out by Dandy et al. (2006), the GHG emissions resulting from pipe manufacturing were evaluated for two different designs of a WDS. To the authors' knowledge, the Dandy et al. (2006) study was the first time that GHG emissions have been evaluated for a WDS design problem in a published paper.

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

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

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

Methods

Multi-Objective Optimization

In order to optimize WDSs accounting for both the economic and environmental objectives, a multi-objective approach is required. A multi-objective approach can be implemented by using a number of different algorithms. Among these algorithms, genetic algorithms have been shown to be effective in solving WDS optimization problems in a study conducted by

Simpson et. al (1994). Since then, genetic algorithms, and later, multi-objective genetic algorithms have been used successfully in solving WDS optimization problems (Savic 2002; Farmani et al. 2005; Keedwell and Khu 2006; Jayaram and Srinivasan 2008).

In this study, a multi-objective genetic algorithm called WSMGA (Water System Multi-objective Genetic Algorithm) was developed based on one of the “state-of-the-art” multi-objective genetic algorithms – NSGA-II (Deb et al. 2002). The optimization procedure using NSGA-II is summarized in Figure 1. In addition to the conventional steps of genetic algorithms, such as selection, crossover and mutation, NSGA-II has four special features (shown in bold in Figure 1), which distinguish it from traditional multi-objective genetic algorithms. First of all, before applying the ranking operation, a global population is generated by combining both the parent and child generations, thus elitism is ensured. Secondly, a special book-keeping strategy is used in the non-dominated sorting process, which reduces computational complexity. In addition, a crowding distance comparison is used for solutions with the same rank; hence a sharing parameter is not required. Furthermore, an efficient constraint handling method referred to as constrained tournament selection (Deb 2002) is used. In this type of tournament selection, the need for a penalty coefficient is removed and feasible solutions are always given priority over infeasible solutions. WSMGA has adopted these four features. In addition, in WSMGA the traditional binary coding scheme in NSGA-II has been modified to handle integer values, which caters for discrete decision variables generally encountered in WDS optimization problems; while the option of using real number inputs in NSGA-II has been preserved. In order to validate its performance, WSMGA was tested by benchmarking it against NSGA-II using a number of the test functions in Deb et al. (2002), for which real number inputs were used.

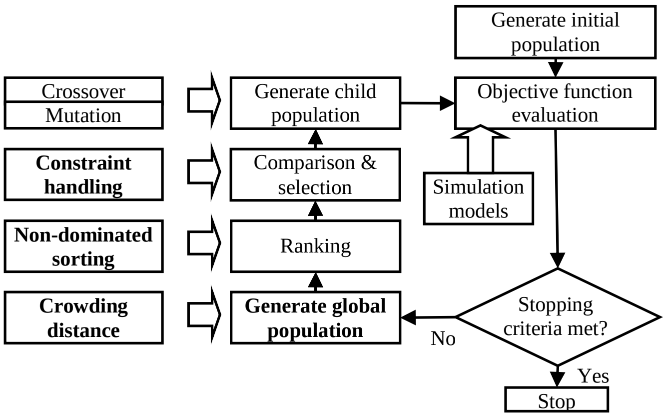

Figure 1 Optimization process using multi-objective Genetic Algorithm NSGA-II

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

Present Value Analysis

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

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

where, C is the payment at a given future time; t is the number of time periods; i is the discount rate. Therefore, PV_t is the present value of a future payment at the end of the t-th time period. In this equation, $\frac{1}{(1+i)^t}$ is the discount factor that represents the extent of the reduction that occurs when a future payment to be received at time t is translated into its present value. The selection of the value of discount rate i is important, as it has significant impact on the results of present value analysis. When dealing with private projects, the discount rate is usually based on the marginal productivity of capital (Dasgupta et al. 1999). However, in the case of dealing with social/public projects, discount rates based on social cost-benefit analysis/social discounting are recommended (Rambaud and Torrecillas 2005).

Social Discounting

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

A zero discount rate has been proposed by a number of authors. Azar and Sterner (1996) suggested that the rate of pure time preference should be zero, and therefore, a zero discount rate should be used if the economic growth declines when the world economy reaches a certain level. Dasgupta et al. (1999) pointed out that if the production activity of humans contributed to too much of the accumulation of "public bad", such as GHG emissions, the discount rate could be zero, or even negative. Constant discount rates ranging from 2% to 10% are most commonly used by current government agencies and organizations (Rambaud and Torrecillas 2005). In addition, in a recent report prepared by Sir Nicholas Stern for the British Government (2006), the author proposed a 1.4% discount rate for a 100-year time horizon in relation to GHG abatement strategies. This 1.4% discount rate is computed based on the feasibility and costs of stabilizing GHG concentrations in the atmosphere within a desired range (to less than 550 ppm) in order to avoid catastrophic climate change. Time declining discount rates, such as Hyperbolic discounting (Henderson and Langford 1998) and Gamma discounting (Weitzman 2001), have also been proposed. However, these discount rates are not widely used in practice. To the authors' knowledge, the UK government is the first government that has adopted a time declining discount rate. In *The Green Book* (Her Majesty's Treasury 2003), a long term discount rate is suggested to be 3.5% for periods within zero to 30 years, declining to 1.0% at year 300 and held constant thereafter. This time declining discount rate is referred to as the HMT discount rate in this paper.

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

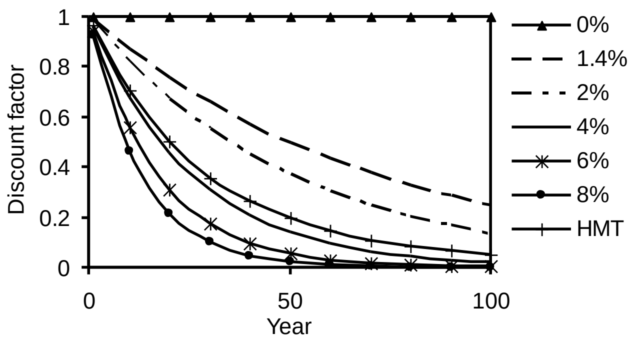

Figure 2 Discount rates and their corresponding discount factors over 100 years

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

Problem Formulation

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

Minimization of Total Cost of Water Distribution Systems

The total cost of a WDS considered in this study consists of capital costs, pump replacement costs and operating costs, as given in Eq.2:

Minimize

$$f_1 = CC + PRC + OC \tag{2}$$

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

Capital Cost: The capital cost is given as:

$$CC = \sum_{i=1}^{npipe} PiC(pipe_i) + \sum_{j=1}^{npump} SC(pump_j) \tag{3}$$

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

Pump Replacement Cost: In this study, a pump service life of 20 years and a system design life of 100 years have been assumed. Therefore, pumps will be replaced four times during the design life of the system, and the pump replacement cost is the sum of the present value (PV) of the pump costs, as given below:

$$PRC = \sum_{j=1}^{npump} PV(PuC(pump_j)) \tag{4}$$

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

Operating Cost: The operating cost is given as:

$$OC = PV(AOC) \tag{5}$$

where, AOC is the annual operating cost. In Eq.5:

$$AOC = ET * AEC \tag{6}$$

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

$$AEC = \frac{P * HR}{\eta_{motor}} = \frac{\gamma QH}{\eta_{pump}} * \frac{HR}{\eta_{motor}} \tag{7}$$

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

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

The total GHG emissions considered in this study consist of capital and operating emissions, as given in Eq.8:

Minimize

$$f_2 = CGHG + OGHG \tag{8}$$

where, $CGHG$ (as defined in Eq.(9)) and $OGHG$ (as defined in Eq.(10)) are the capital and operating GHG emissions, respectively. Capital emissions are due to the manufacture and installation of network components, such as pipes, pumps, valves and tanks. In this study, only pipes are considered as the source of capital emissions. These emissions occur at the beginning of a project. Similarly to the operating costs, operating emissions are due to electricity consumption related to the operation of the system over time. Therefore, the calculation of operating emissions also requires present value analysis.

Capital GHG Emissions: The capital emissions can be calculated using the following equation:

$$CGHG = EF * \sum_{i=1}^{npipe} EE(pipe_i) \tag{9}$$

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

In practice, the embodied energy values and emission factors may also vary across regions and with time, depending on the material excavation and extraction methods used and the makeup of electricity energy sources (for example, thermal, nuclear, wind, hydroelectricity, etc.). In this study, a specific value of the embodied energy for ductile iron cement mortar lined (DICL) pipes of 40.2 MJ/kg is used. This value was estimated by Ambrose et al. (2002) based on a combination of published data and actual factory manufacturing data. It should be noted that the values of embodied energy in MJ/kg need to be interpreted carefully, as different types of pipes have different wall thicknesses and different densities, and therefore need different amounts of material per meter length of pipe to manufacture (Ambrose et al. 2002). Thus, before the embodied energy value in MJ/kg can be used in piping system energy analysis, it needs to be translated into units of MJ/m length by multiplying it by the unit mass (in kg/m) of the pipes. A constant emission factor of 1.042 kg CO_2-equivalent per kWh has been used in this paper. This value is a full fuel cycle emission factor for end electricity users in South Australia (Australian Greenhouse Office 2006). Clearly, this value is an estimate and any analysis should include a sensitivity of the results to a lower or higher value and also the possibility that this value will change with time as a different mix of electricity energy sources evolves into the future due to responses by Governments to global warming.

Operating GHG Emissions: The operating emissions are given as:

$$OGHG = PV(AOGHG) \tag{10}$$

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

$$AOGHG = EF * AEC \tag{11}$$

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

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

Case Study

Case Study Description

For the case study, water needs to be delivered from a water source with an elevation of EL.0.0 to a small town with an elevation of around EL.110 m (Figure 3) via one tank. The network consists of a transmission network and a distribution network. The transmission network consists of a fixed speed main pump, a rising main, a fixed speed booster pump, a transmission main and a storage tank. The distribution network consists of a distribution main, a 4-pipe network and four nodes. There are two possible tank locations and only one location will be selected. Location one (node 10) is on the top of a hill (EL.190 m) and location two (node 11) is on the side of the hill (EL.140 m). Location one is higher, which requires more energy to pump water into the tank; however, it is closer to the town and the higher elevation gives it an advantage in distributing water into the downstream network where smaller pipes should be required. Location two is lower in elevation, but is further away from the town (Table 1). The system needs to be able to deliver at least 80 L/s water at three demand nodes (nodes 6, 7 and 8) in the town during the peak hour (thus a total demand of 240 L/s from the tank). Therefore, the transmission network needs to be able to deliver at least 120 L/s of water to the tank on the peak day (a peak hour factor of 2 has been assumed) (Water Services Association of Australia 2002). The pressure heads at the demand nodes need to be higher than 20 meters in order to provide adequate pressure to residents to perform daily activities. A simplified network has been studied here to demonstrate the framework for considering the trade-offs between costs and GHG emissions. For more realistic applications, other complexities involved in water distribution designs, such as staging and additional demand loading cases (e.g. fire demand loading cases and reliability breakage loading cases), also could be considered. However, it would be straightforward to add these considerations into the simulation runs carried out during the multi-objective optimization analysis. This is one of the advantages of using genetic algorithm analysis, where simulation is an independent component of the optimization process, enabling changes in the system to be accommodated easily.

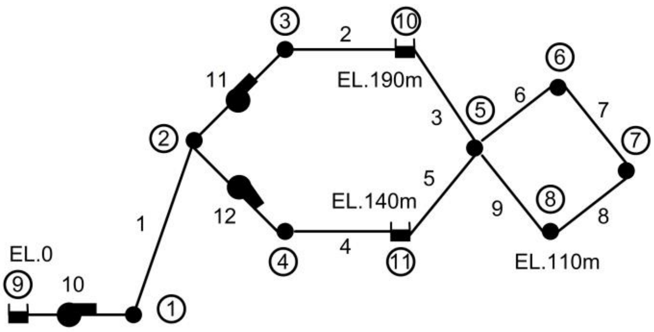

Figure 3 Case study network configuration

Table 1 Pipe lengths for the case study network

Pipe	Length (m)
1	10,000
2	10,000
3	10,000
4	10,000

5	13,000
6	2,000
7	3,000
8	2,000
9	3,000

In this case study, the available options for the decision variables include 30 pump curves for 16 different fixed speed pumps selected using Thompson Kelly & Lewis' pump selection computer program EPSILON and 16 ductile iron cement mortar lined (DICL) pipes of different diameters. Details of the pumps and pipes are given in Tables 2 and 3, respectively. The WSMGA described previously is used to optimize the system for both discount scenarios. Keedwell and Khu (2006) pointed out that the starting position in the search space is important for genetic algorithms to find desired solutions in multi-objective optimization. Consequently, 100 random seeds (i.e. random starting positions) have been used in this paper to ensure near-globally optimum solutions are found.

Table 2 Pump information for the case study network

No.	Pump Type	Speed (rpm)	Impeller Dia. (mm)	BEP* (%)	Q at BEP (L/s)	H at BEP (m)	Rated Power (kW)	Station Cost (10^3\$)	Pump Cost (10^3\$)
1A	8*17A_ECS-2s	1475	410	83	126	107	159	990	644
1B	8*17A_ECS-2s	1475	432	83	130	120	183	1,086	723
2A	8*17B-3s	1475	393	82	112	118	158	988	643
2B	8*17B-3s	1475	445	84	130	154	233	1,263	875
3A	8*17B_ECS-2s	1475	445	84	130	104	158	985	640
4A	8HN124A	2950	293	79	175	95.9	209	1,181	803
4B	8HN124A	2950	318	81	189	119	272	1,384	985
5A	6LG13/A	2900	311	80	109	117	155	975	633
5B	6LG13/A	2900	321	81	113	125	171	1,039	684
6A	430DMH-4s	1480	275	84	157	94.6	173	1,047	690
6B	430DMH-4s	1480	312	85	180	121	251	1,320	926
7A	430DMH-5s	1480	251	84	142	99.2	164	1,011	662
7B	430DMH-5s	1480	312	85	180	151	313	1,502	1,097
8A	430DML-5s	1480	290	82	131	101	159	989	644
8B	430DML-5s	1480	313	82	140	118	197	1,138	767
9A	430DML-6s	1480	272	81	123	107	158	988	643
9B	430DML-6s	1480	313	82	140	142	238	1,277	888
10A	460CDKH-4s	1480	280	81	183	93.5	206	1,169	793
10B	460CDKH-4s	1480	336	83	220	134	348	1,593	1,187
11A	460DKL-3s	1480	334	85	182	87	182	1,081	719
12A	460DKL-4s	1480	295	84	162	90.7	171	1,038	683
12B	460DKL-4s	1480	336	85	185	116	247	1,306	914
13A	510DML-3s	1480	332	80	220	83.4	226	1,238	853

13B	510DML-3s	1480	369	81	240	104	301	1,469	1,065
14A	510DMH-6s	980	339	83	197	88.3	204	1,164	788
14B	510DMH-6s	980	368	83	215	103	261	1,350	954
15A	200*300-630	1480	537	81	192	97.1	224	1,233	849
15B	200*300-630	1480	635	83	230	135	367	1,641	1,235
16A	250*300-500B	1480	553	84	273	93.9	298	1,461	1,057
16B	250*300-500B	1480	562	84	275	97.3	311	1,496	1,091

*BEP: Best efficiency point

Table 3 Ductile iron cement mortar lined (DICL) pipe information for the case study network

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

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

Optimization Results from Discount Scenario 1 (Greenhouse Gases Always Discounted at Zero Rate)

All of the Pareto-optimal fronts obtained from the first discount scenario using different discount rates for costs (zero, 1.4%, 2%, 4%, 6%, 8% and declining (HMT)) are plotted in

Figure 4. In this discount scenario, both high tank solutions and low tank solutions (contained in the ovals in Figure 4) are found on the optimal front, no matter which discount rate is used. In general, high tank solutions have lower cost but higher GHG emissions compared to low tank solutions. It is evident from the figure that the discount rate used has a significant impact on the optimal front. As the discount rate for costs increases, the optimal fronts switch towards the left on the graphs in Figure 4. This is because when a high discount rate is used, the future costs (including operating costs and pump replacement costs) are heavily discounted, which results in lower total costs. However, compared to the total costs of the optimal solutions, the total GHG emissions generated from the networks, especially low tank networks, are less sensitive to the discount rate used for calculating ongoing costs. GHG emissions generated from all low tank solutions are within a similar range (220 to 240 kilotonnes), as most of the constant discount rates for costs (from zero to 6%) lead to the same set of low tank solutions on the optimal fronts. Whereas for high tank solutions, when the discount rate is increased to a certain level, in this case 6% and higher, networks with extremely high emissions (solutions contained in the circle in Figure 4(b)) are introduced into the optimal front due to their low costs.

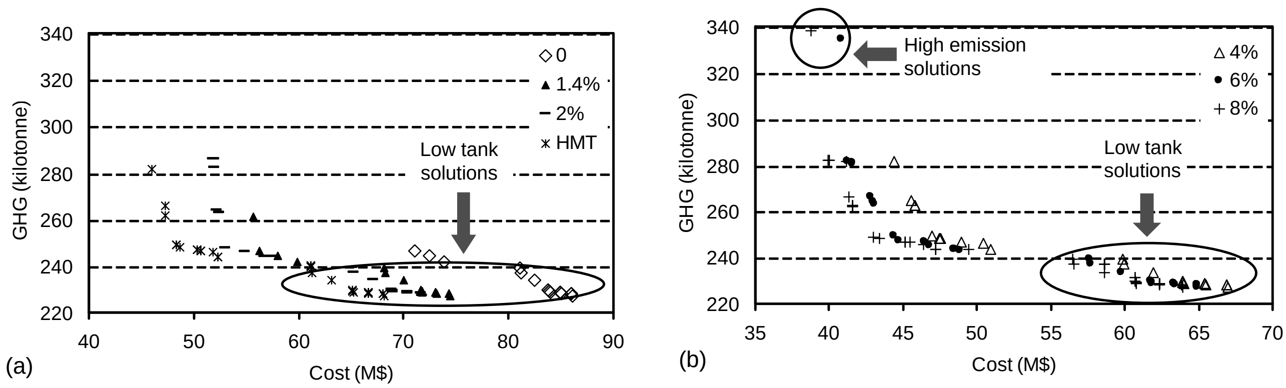

Figure 4 Optimization results from discount scenario 1 (GHG emissions not discounted): (a) Optimal front obtained using discount rates of zero, 1.4%, 2% and the HMT time declining discount rate; (b) Optimal front obtained using discount rates of 4%, 6% and 8%

The optimization results obtained in this discount scenario also show that the inclusion of GHG emission minimization as one of the objectives results in significant trade-offs between the economic and environmental objectives. The trade-offs obtained using the discount rates of 1.4% and 6% are presented in Figures 5(a) and 5(b), respectively. These trade-offs provide decision makers with an improved understanding of the objective space. When a discount rate of 1.4% is used, 19 solutions (four high tank solutions and 15 low tank solutions) are found along the optimal front. When a discount rate of 6% is used, thirty solutions (15 high tank solutions and 15 lower tank solutions) are found on the optimal front. The network configurations of a number of typical solutions for each discount rate are provided in Table 4. The last column of Tables 4 shows the percentage of operating energy that is used to overcome friction losses in the corresponding networks. The costs and emissions from these solutions are summarized in Table 5. Table 5 and Figure 5(a) show that when a discount rate of 1.4% is used, from the lowest cost solution (design A) to the second lowest cost solution (design B), a \$0.6 million increase in cost results in a 15 kilotonnes reduction in GHG emissions. This is equivalent to \$40/tonne of GHGs in the form of carbon dioxide equivalent (CO_2-e) (Figure 5(a)). However, from design B to design C (the lowest emission high tank solution), the cost of reducing one tonne of GHGs is increased to \$720/tonne CO_2-e. The low tank solutions, such as designs D (the lowest cost low tank solution) and E (the lowest emission low tank solution) generate fewer GHG emissions compared to the high tank solutions. However, these low tank solutions are much more expensive, which also lead to higher costs for reducing every tonne of GHG emissions. The trade-offs between the two objectives can vary when different discount rates are used. When a discount rate of 6% is used, Table 5 and Figure 5(b) show that from the lowest cost solutions (design F) to the second lowest cost solutions (design G), a \$0.4 million increase in cost leads to a 53 kilotonnes decrease in GHG emissions, which equals to only \$7.5/tonne of CO_2-e (Figure

5(b)). However, from design G to design H, the cost to reduce one tonne of GHGs is increased to \$97/tonne of CO_2-e. From design H to the lowest cost high tank solution (design I), the cost is further increased to \$643/tonne of CO_2-e.

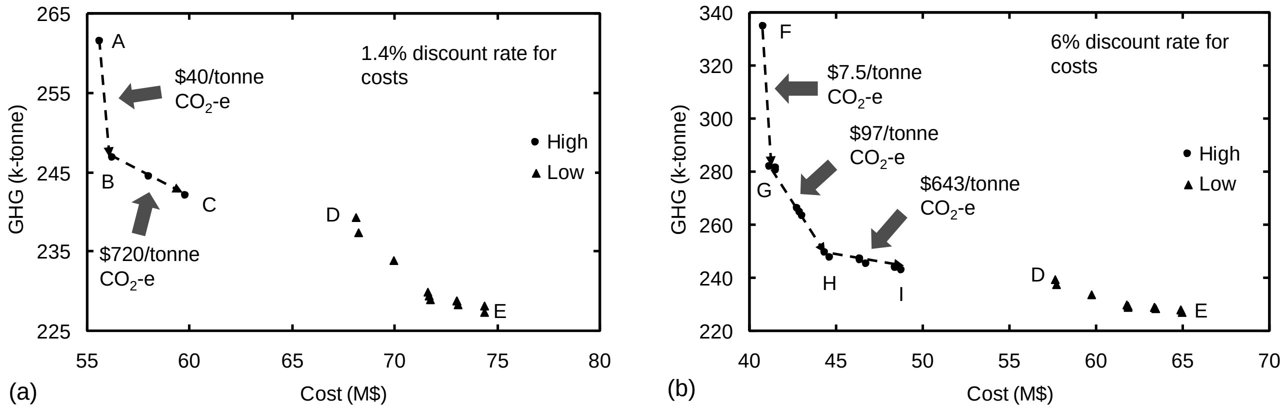

Figure 5 (a) Optimal solutions obtained using the discount rate of 1.4%; (b) optimal solutions obtained using the discount rate of 6%

Table 4 Network configurations and characteristics of solutions obtained in discount scenario 1

Disc. Rate	No.	Pump No.1 & No.2	Pump No.1 & No.2 Efficiency	TL*	Pipe Diameter (mm)							Flow (L/s)	Annual Operating Hours	Proportion of operating energy used for overcoming friction
					1	2 or 4	3 or 5	6	7	8	9			
1.4%	A	3A, 1B	83%, 82%	H	375	450	450	300	150	300	450	121	5,812	18%
	B	3A, 3A	83%, 83%	H	450	450	450	300	150	300	450	123	5,682	12%
	C	3A, 3A	84%, 84%	H	525	525	450	300	150	300	450	133	5,252	7%
	D	3A, 3A	81%, 81%	L	450	450	675	450	100	450	600	151	4,638	21%
	E	11A, 11A	83%, 83%	L	600	600	675	450	100	450	600	201	3,478	10%
6%	F	2B, 2B	83%, 83%	H	375	300	450	600	300	100	300	123	5,716	41%
	G	2B, 8A	84%, 81%	H	375	375	450	300	150	300	450	128	5,478	27%
	H	3A, 8A	83%, 81%	H	450	450	450	300	150	300	450	123	5,701	12%
	I	3A, 3A	84%, 84%	H	525	525	450	600	300	100	300	133	5,252	7%
	D	3A, 3A	81%, 81%	L	450	450	675	450	100	450	600	151	4,638	21%
	E	11A, 11A	83%, 83%	L	600	600	675	450	100	450	600	201	3,478	10%

*TL: Tank Location; H: High tank; L: Low tank

Table 5 Different components of objective function values of solutions obtained in discount scenario 1

Disc. Rate	No.	Capital Cost (M$)	Pump Cost Over 100 Years (M$)	Annual Operating Cost (M$)	Operating Cost Over 100 Years (M$)	Total Cost (M$)	Capital GHG (kilotonne)	Annual Operating GHG (kilotonne)	Operating GHG over 100 Years (kilotonne)	Total GHG (kilotonne)
1.4%	A	37.2	2.85	0.29	15.6	55.6	49.6	2.12	212	262
	B	39.3	2.68	0.27	14.3	56.2	52.7	1.94	194	247
	C	43.6	2.68	0.25	13.5	59.8	59.2	1.83	183	242
	D	53.2	2.68	0.23	12.1	68.1	74.3	1.65	165	239
	E	61.1	3.01	0.19	10.3	74.4	87.6	1.40	140	227
6%	F	33.4	0.79	0.40	6.62	40.8	44.6	2.90	290	335
	G	35.1	0.68	0.32	5.37	41.2	46.6	2.35	235	282
	H	39.3	0.58	0.27	4.49	44.3	52.7	1.97	197	250
	I	44.0	0.57	0.25	4.17	48.8	60.2	1.83	183	243
	D	53.2	0.57	0.23	3.76	57.6	74.3	1.65	165	239
	E	61.1	0.65	0.19	3.19	64.9	87.6	1.40	140	227

As the discount rate used has a significant impact on the trade-offs between the two objectives, the use of different discount rates can lead to different final solutions. For example, design B in Figure 5(a) and design G in Figure 5(b) provide reasonable trade-offs between total cost and GHG emissions, as they correspond to the break points in the objective space where the marginal returns are diminishing. Tables 4 and 5 show that they are different solutions. The capital cost of design G is $4.2 million lower compared to design B due to the smaller pipes selected for the upstream network. However, the annual operating cost and emissions of design B are much lower, which lead to 35 kilotonnes less GHGs generated over 100 years compared with design G.

Optimization Results from Discount Scenario 2 (Costs and Greenhouse Gases Discounted at the Same Rate)

The optimal fronts obtained from discount scenario 2 are plotted in Figure 6. Similar results have been found for this discount scenario as for discount scenario 1 in that the inclusion of GHG emission minimization as one objective results in significant trade-offs between the two objectives. Figure 6 shows that in all of the optimal fronts found using different discount rates, the total costs increase as the GHG emissions decrease, as expected.

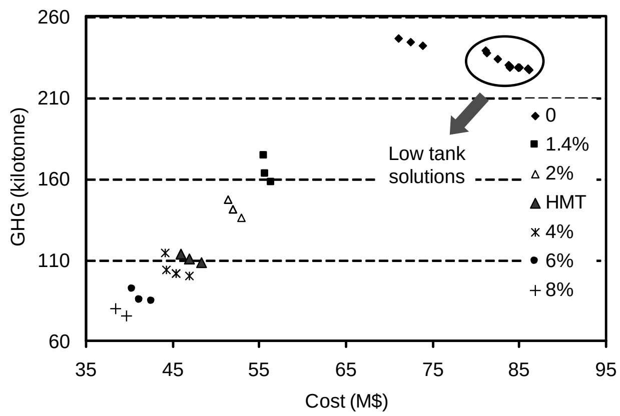

Figure 6 Optimisation results from scenario 2 (both costs and GHGs discounted)

The discount rate used also has a significant impact on the optimization results obtained in this discount scenario. Apart from the impact of the discount rates described in the preceding section, the impact of discount rates in this scenario manifests itself in two other ways. First of all, as the discount rate used increases, the number of solutions on the optimal front decreases. When a zero discount rate is used for both costs and GHGs, there are 18 solutions on the optimal front. They include the lowest cost solution, the lowest emission solution and 16 solutions in-between. However, when the discount rate is increased to 8%, only two extreme solutions remain on the front. This is because a high discount rate discounts both the future cost and emissions heavily in this discount scenario. As a result, the capital components dominate both objective function values and the trade-offs between the two objectives are reduced.

Secondly, the discount rate used has an impact on the tank location that is selected. When a zero discount rate is used, both high and low tank solutions are found on the optimal front. However, once both the future costs and emissions are discounted, the low tank solutions disappear from the optimal front. This can be explained by comparing the components of objective function values of high and low tank solutions. Figure 7 shows the different components of the objective function values of the optimal solutions obtained by using a zero discount rate. Solution 1 is the lowest cost solution and solution 18 is the highest cost solution. Solutions 1 to 3 are high tank solutions, and the rest are low tank solutions. It is evident that capital costs make the biggest contribution to the total costs. High tank solutions have a lower total cost, mainly due to their lower capital costs. In contrast, operating emissions make the biggest contribution to the total emissions. As a result, lower tank solutions have lower total emissions due to their lower operating emissions.

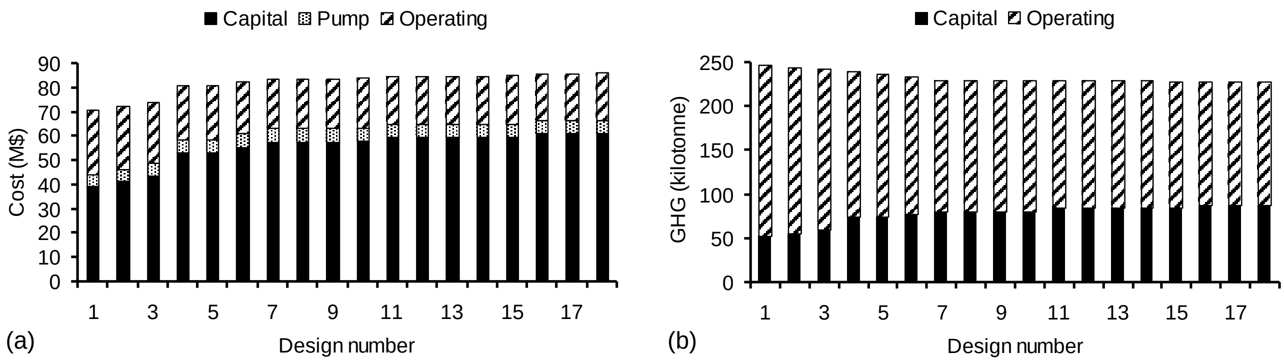

Figure 7 (a) Composition of total costs; (b) Composition of total GHG emissions (Design 1 and Design 18 are the minimum cost and minimum GHG emission solutions obtained using a zero discount rate in discount scenario 2, respectively)

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

Summary and Conclusions

In this paper, a multi-objective approach has been used for optimizing the design of WDSs. In addition to the traditional economic objective (minimization of total life cycle cost), an environmental objective (minimization of GHG emissions) has been taken into account. The results for the case study show that the inclusion of GHG emission minimization as one objective results in significant trade-offs in the form of a Pareto-optimal front between the economic and environmental objectives. Often, an increase in cost that is deemed reasonable and acceptable can result in a substantial reduction in GHG emissions. The case study shows that the cost to reduce GHG emissions can be as low as \$7.5/tonne of CO_2-e. In addition, a significant advantage of multi-objective optimization over single-objective optimization is that the multi-objective optimization results can be presented as a Pareto-optimal front. On the Pareto-optimal front, the points of diminishing marginal returns are clearly evident, where a large increase in cost only produces a relatively small decrease in GHGs. The Pareto-optimal front significantly improves the designer's understanding of the search space and shows which design gives the biggest "bang for the buck" in reducing GHGs.

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

In conclusion, this study has investigated the multi-objective trade-offs between the cost and GHG emissions from WDSs and has explored the sensitivity of the multi-objective optimization results to the discount rates used. In this study, a simply hypothetical case study has been used. Based on the trade-offs obtained from the simple network, the framework to evaluate GHG emissions from WDSs, which have been developed in this paper, can now be tested on larger and more realistic WDSs. In addition, since the results in this paper are based on a number of assumptions, a sensitivity study incorporating the uncertainties of the parameters, such as emission factors and embodied energy factors, into the optimization could be a future research direction. Optimization is used in this paper as an explorative tool to investigate new, innovative solutions to a problem with increased complexity due to the consideration of GHG emissions. Engineering judgment is still necessary in making the decision about which network is finally selected.

Acknowledgements

This research was supported by resources supplied by eResearch SA. The authors also would like to thank the reviewers, including Dr. Tom Walski and the other two anonymous reviewers, for their detailed comments. The paper has been improved as a result.

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