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

Wenyan Wu

School of Civil, Environmental and Mining Engineering, University of Adelaide,
Adelaide, 5005, Australia

wwu@civeng.adelaide.edu.au

Holger R. Maier

School of Civil, Environmental and Mining Engineering, University of Adelaide,
Adelaide, 5005, Australia

hmaier@civeng.adelaide.edu.au

Angus R. Simpson

School of Civil, Environmental and Mining Engineering, University of Adelaide,
Adelaide, 5005, Australia

asimpson@civeng.adelaide.edu.au

Abstract: Previous research has demonstrated that there are significant trade-offs between the competing objectives of minimizing costs and Greenhouse Gas (GHG) emissions for water distribution system (WDS) optimization. However, upon introduction of an emissions trading scheme, GHG emissions are likely to be priced at a particular level. Thus, a monetary value can be assigned to GHG emissions, enabling a single-objective optimization approach to be used. This raises the question of whether the introduction of carbon pricing under an emissions trading scheme will make the use of a multi-objective optimization approach obsolete or whether such an approach can provide additional insights that are useful in a decision-making context. In this paper, the above questions are explored via two case studies. The optimization results obtained for the two case studies using both single-objective and multi-objective approaches are analyzed. The

analyses show that the single-objective approach results in a loss of trade-off information between the two objectives. In contrast, the multi-objective approach provides decision makers with more insight into the trade-offs between the two objectives. As a result, a multi-objective approach is recommended for the optimization of WDSs accounting for GHG emissions when considering carbon pricing.

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

Introduction

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

considerations into the optimal design and operation of water distribution systems (WDSs).

GHG related issues, such as energy consumption, have been investigated in many studies in WDS research. In the area of optimization, Sarbu and Borza (1998) investigated various solutions to increasing the power efficiency of pumping systems. Baran et al. (2005), Lopez-Ibáñez et al. (2005) and Ulanicki et al. (2007) optimized the scheduling of pumps to reduce electricity costs. In the planning and management area, Lundie et al. (2004) developed a life cycle assessment approach for metropolitan water system planning, in which energy use and direct gaseous emissions are identified as two of the important environmental indicators of a sustainable metropolitan water systems. Filion et al. (2004) also employed a life cycle approach to quantify energy expenditures of pipes in a WDS. More recently, Filion (2008) explored the connections between the urban form and energy use of water distribution networks. In a study carried out by Dandy et al. (2006), GHG emissions resulting from pipe manufacturing were evaluated for a WDS. Following the Dandy study, Wu et al. (2010) considered the impact of GHG emissions on the optimal design of WDSs explicitly, by incorporating the minimization of life cycle GHG emissions, together with the minimization of system costs, into the optimal design of WDSs via a multi-objective approach. It is now becoming increasingly common for carbon related emissions to be priced under an emissions trading scheme, yet the impact of carbon pricing on the optimal design and operation of WDSs has not been investigated thus far.

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

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

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

Methods

Objective Function Evaluation

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

Figure 1 shows the objective function evaluation process. The system cost considered in this study is defined as the sum of the capital costs, operating costs for pumping and pump replacement/refurbishment costs at regular intervals during the service or design life of the system. The capital cost is incurred due to the purchase and installation of network components (pipes and pumps) and construction of pump stations. This cost occurs at the beginning of a project. As the design life of a WDS is much longer than the service life of pumps, then pumps and electrical control equipment need to be replaced or refurbished periodically to ensure the performance of the system is maintained. In the

case studies in this paper, a 100-year pipe network service life and a 20-year pump service life are assumed. The operating cost is incurred mainly due to the system operation of pumping. The computation of the annual operating cost is taken as the annual energy consumption multiplied by an average electricity tariff. A motor efficiency of 95% is assumed for each pump. In practice, electricity tariffs may vary across regions and with time. In this study, an electricity cost of 0.143 dollars per kWh is assumed, which is an approximate average electricity tariff taking into account peak and off-peak tariffs. As both pump replacement/refurbishment costs and operating electricity costs occur during the life of the system, calculation of these two costs requires present value analysis.

In calculating the annual energy consumption, a 48-hour extended period simulation (EPS) has been used in the simulation model to account for the diurnal variation in demand, the fluctuation in tank water levels and the variation of the pump operating point during the day, to provide a realistic estimate of the operational behavior of the system. In the EPS, a diurnal demand curve presented in Figure 2 applied to the average flow during a year or the average-day flow (Water Services Association of Australia 2002) is used to estimate the average energy consumption of the system due to pumping during the design period (100 years). In addition, an average flow on the peak day is used to design the distribution systems upstream of the balancing storage tanks, as suggested by Water Services Association of Australia (2002). The average flow on the peak day is computed by multiplying the average-day flow by the Peak Day Factor (PDF). In this paper, a PDF of 1.5 obtained from the Water Services Association of Australia (2002) is

used. It should be noted that in designing distribution systems downstream of the balancing storage tanks, the average flow on the peak hour and fire loading cases would also be required to ensure an adequate design. In both case studies, an average pipe roughness value of $\epsilon=0.25\text{mm}$ was assumed for the first 50-year period and a value of $\epsilon=1.5\text{mm}$ for the second 50-year period in order to account for pipe aging.

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

In addition, in evaluating the capital emission costs, embodied energy analysis (EEA) is first applied to translate the material use of the pipes into an estimate of their embodied energy in MJ. Thereafter, emission factor analysis (EFA) is used to translate embodied energy use into a corresponding estimate of GHG emissions in kg of $\text{CO}_2\text{-e}$ (carbon

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

Optimization Approach

In this paper, a multi-objective genetic algorithm (GA) is used, as GAs have been shown to be effective for WDS optimization problems (Simpson et al. 1994). GAs are a global optimization method that belong to the class of evolutionary algorithms (Goldberg 1989). GAs differ from traditional optimization techniques in that the concept of GAs is inspired by natural phenomena of heredity. GAs use the “principle of survival of the fittest” to select more suitable trial solutions by dealing with a population of solutions simultaneously. Each solution is represented by a binary, integer or real valued string

called a chromosome. By applying three genetic operators: selection, crossover and mutation to the chromosomes, GAs maintain good solutions in the current population of solutions and explore the search space for better solutions. The search process terminates when the stopping criteria are met.

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

Carbon Pricing

Emissions trading is one of the most popular schemes for controlling GHG emissions. In most emissions trading schemes, a cap and trade approach is used. Under a cap and trade approach, emission permits are usually issued by the government. Businesses must have

sufficient permits to cover the GHG emissions they produce each year. These permits can be sold or purchased in the marketplace (The Task Group on Emissions Trading 2007). Ideally, the carbon price is based on the social cost of carbon, which normally refers to the cost to mitigate climate change (reduce GHG emissions) or the marginal social damage from a tonne of emitted carbon (Guo et al. 2006). However, the actual carbon price is often determined by the market (The Task Group on Emissions Trading 2007). The average world market price of a tonne of GHGs in the form of CO₂-e in 2005-06 was around \$US20 - \$US25 (Mitchell et al. 2007). In order to achieve long-term abatement, the carbon price is expected to rise over time (The Task Group on Emissions Trading 2007). In the literature, there are many estimates of possible future carbon prices based on different scenarios. The Australian Bureau of Agricultural and Resource Economics (ABARE) estimates carbon prices to range from \$A28 to \$A46 per tonne of CO₂-e for an international market and from \$A15 to \$A31 per tonne of CO₂-e for an Australian abatement market in 2030 (The Task Group on Emissions Trading 2007). However, the actual social cost of carbon could be higher. Sterner and Persson (2007) suggest that a marginal social cost of carbon could reach over \$US400 per tonne of C (carbon) by 2050, which is equivalent to about \$US110 or \$A120 per tonne of CO₂-e. As a result, four carbon prices ranging from \$A10 to \$A120 per tonne of CO₂-e (\$A10, \$A30, \$A60 and \$A120) have been used in this paper. It should be noted that actual market carbon prices will vary with time. However, the constant carbon prices adopted in this paper are sufficient to illustrate the impact different carbon prices are likely to have on the trade-offs between cost and GHG emissions, as they cover the likely range of expected values.

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

Present Value Analysis

In economics, time preference is generally accounted for by using present value analysis (PVA) (Tietenberg 1997). In practice, a discount rate equal to the cost of capital (around 6 to 8%) is usually used. However, in the planning of social projects, such as WDSs, PVA with a discount rate that represents the social cost is required to translate the costs from far in the future to the present, enabling effects occurring at different times to be compared. The selection of appropriate discount rates for projects with long term social and/or environmental impacts, which will potentially be spread out over hundreds of years, remains a controversial issue. For traditional project planning, in which only economic costs are considered, the controversy mainly lies in selecting the correct discount rate. However, for a multi-objective design, such as the situation described in this paper, the controversy is twofold. The first issue is selecting the correct discount rate and the second issue is whether or not the discount rate used for one design objective, such as economic costs, should also be used for the other design objective, such as GHG emissions.

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

Case Studies

Case Study 1

Case Study 1 Description: The network configuration for this system is shown in Figure 3 and the design conditions are summarized in Table 1. The aim of the design is to select the best combination of pump and pipe sizes that minimize both the system cost and GHG emissions of the network. In the optimization process, the following demand loading cases are used to select appropriate networks:

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

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

In this paper, seventeen different pump curves for 10 different fixed speed pumps (some pumps have two curves) and 26 ductile iron cement mortar lined (DICL) pipes of different diameters are considered as options in this case study. The pump curves were selected using Thompson Kelly & Lewis' pump selection program EPSILON (2001). The initial pump station cost is taken as part of the capital cost and the pump cost has been used to compute pump replacement/refurbishment costs. The costs of the pumps and corresponding pump stations have been calculated according to the sizes of the pumps (Wu et al. 2008). The mass per unit length of the pipes is calculated according to DICL pipe data obtained from Tyco Water. Details of the pumps and pipes are given in Tables 2 and 3, respectively.

Results from Case Study 1: The search space for this case study has only 442 solutions. Therefore, instead of genetic algorithm optimization, full enumeration and non-dominated sorting of all enumerated solutions have been used to optimize this system. As a result, the optimization results are true Pareto-optimal solutions. A total of eight solutions were found along the Pareto-optimal front for this case study. These solutions are denoted as numbers 1 to 8 in order of increasing initial capital cost of the pipelines. The larger the number is, the larger the capital cost of the pipeline. The network configuration and characteristics of these eight solutions found on the Pareto-optimal fronts are summarized in Table 4. The Pareto-optimal fronts and the single-objective optimal solutions obtained for each of the different carbon prices are plotted in Figure 4. The numbers next to the solution points in Figure 4 are the corresponding design numbers in Table 4. The single-objective optimal solutions are represented with an unfilled symbol. For example, in Figure 4(a), Design 2 is the second lowest system cost solution found when a carbon price of \$10/tonne of CO₂-e is used in the multi-objective optimization. The diameter of the pipe is 375 mm as shown in Table 4. Design 2 is also the lowest total cost solution obtained using the single-objective approach with the same carbon price. The water level fluctuation in the tank and the variation of the flow over the 48-hour EPS period for Designs 1 and 8 are also plotted in Figure 4.

In the single-objective optimization, as expected, only the least total cost network is found for each carbon price considered, as shown by the unfilled symbol solutions in Figure 4. The single-objective optimal solution is dependent on the carbon price used and higher carbon prices tend to result in solutions with larger pipes, as expected. Figure 4

shows that carbon prices of \$10, \$30 and \$60/tonne CO₂-e lead to an optimal design with a pipe diameter of 375 mm (Design 2 in Figures 4(a), 4(b) and 4(c)), while the higher carbon price of \$120 per tonne of CO₂-e results in an optimal solution with a pipe of 450 mm in diameter (Design 3 in Figure 4(d)). This is because the increase in carbon price increases the impact the GHG cost has on the total cost. Consequently, when a higher carbon price is used, a network with larger pipe size, which has less friction loss and generates fewer operating GHG emissions, is more likely to be selected.

Figure 4 shows that in the multi-objective optimization, an ordered set of Pareto-optimal solutions is found for each carbon price considered. These Pareto-optimal solutions include the lowest system cost solution, the lowest GHG emission cost solution, and other non-dominated solutions in-between. These Pareto-optimal solutions show significant trade-offs between the two objectives. When a carbon price of \$10 per tonne of CO₂-e is used (see Figure 4(a)), from Design 1 (the lowest system cost solution) to Design 2, a \$13,100 increase in system cost results in a \$147,000 reduction in GHG emission cost. From Design 2 to Design 3, a \$288,000 increase in system cost results in a \$26,100 reduction in GHG cost. From Design 3 to Design 6, a \$373,000 increase in system cost only results in a \$14,000 reduction in GHG cost. These trade-offs are highly carbon price dependent, as expected. For example, Figure 4(d) shows that when the carbon price is increased to \$120/tonne of CO₂-e, from Design 1 to Design 2, a \$13,100 increase in system cost leads to a \$1.77 million decrease in GHG costs, which is more than \$1.6 million higher than the decrease in GHG costs when a carbon price of \$10/tonne of CO₂-e is used. It should be noted here that the optimization results also rely

on the discount rate used. However, this is not the focus of this study and as mentioned previously, details of the impact of different discount rates on the trade-offs between costs and GHG emissions are given in Wu et al. (2010).

In addition, in the multi-objective optimization, it has been found that the carbon price used has no impact on the ordered set of optimal solutions that are spread out along the Pareto front. Figure 4 shows that the same ordered set of Pareto-optimal solutions is found no matter which carbon price is used. This is because the carbon price here only changes the scale of the second objective function values; however, it does not have any impact on the relative ranking of the Pareto-optimal solutions found for this case study. Therefore, the trade-offs between the two objectives can also be represented by the dollar cost to reduce GHG emissions by one tonne, as shown in Figure 5. The trade-offs represented by the dollar cost per tonne of GHGs are independent of the market carbon price used. For example, to move from Design 1 to Design 2, a \$13,100 increase in the system cost results in an 14.8 kilotonnes reduction in GHG emissions over the design life of the system, which can be calculated from the information provided in Table 4. Therefore, the cost to reduce one tonne of GHG emissions from Design 1 to Design 2 is equal to \$0.89/tonne CO₂-e, as shown in Figure 5. This cost is increased to \$110/tonne CO₂-e from Design 2 to Design 3, and \$266/tonne CO₂-e from Design 3 to Design 6. This presentation of the trade-offs leads to a new way of identifying the single-objective optimal solution by using a carbon cost mapping of the optimal solution space, as shown in Figure 5.

In order to obtain this carbon cost mapping, a convex optimal front needs to be defined from within the Pareto-optimal front. A convex optimal front is the set of piece-wise linear lines connecting the non-dominated solution points, for which the sequence of slopes is non-decreasing. By calculating the dollar cost to reduce one tonne of GHG emissions between two adjacent solutions on the convex optimal front, a carbon cost mapping of the optimal solution space can be obtained. With this carbon cost mapping, the single-objective optimization solution (or the lowest total cost solution) for a given market carbon price can be found easily without the need for any additional optimization runs. For example, for this case study, when the carbon price is between \$0.89 and \$110/tonne CO₂-e (see Figure 5), Design 2 with a pipe size of 375 mm is the single-objective optimal solution (see Figures 4(a) to 4(c)); and when the carbon price is between \$110 and \$266/tonne CO₂-e (again see Figure 5), Design 3 with a pipe size of 450 mm is the single-objective optimal solution (see Figure 4(d)).

Case Study 2

Case Study 2 Description: The network configuration of the second case study is shown in Figure 6. The network consists of a water source (reservoir 6), a pump, eight pipes and three tanks, each of which has an initial water level of 90 m. The aim of this case study is to minimize both system cost and GHG emissions of the network, while being able to deliver at least the average flow on the peak day to each tank. In the optimization process, the same demand loading cases as those used in the first case study are used to select appropriate networks for this case study. The design conditions are summarized in Table 5. The options for the pump are the same as those presented in Table 2. The sizes of the

pipes can only be selected from the first 16 choices presented in Table 3, as the larger pipes were identified as being too big and were therefore not considered in the optimization analysis.

Results from Case Study 2: The WSMGA computer optimization program was used to optimize the second network. In the GA optimization process, a population size of 500, 3000 generations, a crossover probability of 0.9 and a mutation probability of 0.1 were used. These GA parameter values were selected using a series of sensitivity tests, in which the combination of the parameter values generated consistent Pareto-optimal fronts within a reasonable execution time. Keedwell and Khu (2006) pointed out that the starting position in the search space is important in order for multi-objective genetic algorithms to find desired solutions. Consequently, one hundred random seeds (i.e. random starting positions) have been used in this study to assess the consistency of the performance of WSMGA.

The Pareto-optimal fronts and the single-objective optimal solutions for the second case study obtained using different carbon prices are plotted in Figure 7. The single-objective optimal solutions are again represented with unfilled symbols. The network configurations of six typical convex solutions found in this case study are presented in Table 6. The pipeline cost, annual energy consumption and GHG emissions of these solutions are presented in Table 7. These solutions are ranked from 1 to 6 according to the initial capital cost of the pipelines. The larger the number is, the larger the initial

capital cost of the pipelines. The numbers next to the solution points in Figure 7 are the corresponding design numbers in Tables 6 and 7.

In the single-objective optimization, the carbon price used has a significant impact on the results. As found in the first case study, higher carbon prices tend to result in solutions with larger pipes. For example, Figure 7 shows that a carbon price of \$10/tonne CO₂-e results in a single-objective optimal solution with pipe cost of \$3.52 M (Design 2 in Table 7); while a carbon price of \$30 or \$60/CO₂-e leads to a solution with pipe cost of \$4.10 M (Design 3 in Table 7). When the carbon price is further increased to \$120/tonne CO₂-e, a network with a pipe cost of \$4.15 M (Design 4 in Table 7) is selected.

Similarly to the first case study, an ordered set of optimal solutions is found for each carbon price used in the multi-objective optimization. These optimal solutions also show significant trade-offs between the two objectives. Figure 7(a) shows that when a carbon price of \$10/tonne of CO₂-e is used, from Design 1 (the lowest system cost solution) to Design 2 (the second lowest system cost solution), a \$12,100 increase in system cost results in a \$81,400 decrease in GHG emission cost; from Design 2 to Design 3, a \$266,000 increase in system cost results in a \$101,000 reduction in GHG emission cost; and from Design 3 to Design 4, a \$44,400 increase in system cost only leads to \$6,480 decrease in GHG costs. Similar results can also be found between Designs 4 and 5. These trade-offs are also highly carbon price dependent. Figures 7(b), 7(c) and 7(d) show that when the carbon price increases, the reduction in GHG costs resulting from the same amount of savings in system cost increases accordingly, as would be expected.

As for the first case study, the carbon price used does not have an impact on the relative ranking of the multi-objective optimal solution sets. Therefore, the trade-offs presented in terms of the dollar costs to reduce one tonne of CO₂-e are again carbon price independent. As shown in Figure 8, the cost to reduce one tonne of GHGs is \$1.5/tonne from Design 1 to Design 2, \$26/tonne from Design 2 to Design 3, \$68/tonne from Design 3 to Design 4 and \$124/tonne from Design 4 to Design 5, no matter which carbon price is used. Thus, a carbon cost mapping of the optimal solutions space for this case study is obtained. When the carbon price is between \$1.5 and \$26/tonne CO₂-e (see Figure 8), Design 2 is the single-objective optimal solution (see Figure 7(a)); when the carbon price is increased to \$30 and \$60/tonne CO₂-e, which is between \$26 and \$68/tonne CO₂-e, Design 3 is the single-objective optimal solution (see Figures 7(b) and 7(c)); and when the carbon price is between \$68 and \$124/tonne CO₂-e (again see Figure 8), Design 4 is the single-objective optimal solution (see Figure 7(d)). It should be noted here that the solutions between Designs 2 and 3 (see Figure 8) are not selected. This is because these solutions are not on the convex optimal front. For the same reason, the solutions between Designs 4 and 5 are not selected.

Discussion

The results from both case studies show that both single-objective and multi-objective approaches have advantages and disadvantages. The single-objective approach is easier to implement and results in a simpler decision making process. In contrast, the multi-

objective approach requires more computational effort, as well as domain knowledge and judgment, in order to make a decision. However, the single-objective approach also has significant drawbacks compared to the multi-objective approach.

First of all, in the single-objective approach an implicit weighting is introduced into the objective function evaluation process when the two objectives are converted into one combined objective. Thus, this approach results in a loss of information between the two conflicting objectives (i.e. information about the relative trade-offs between objectives at various carbon prices is lost). Secondly, even though the trade-offs between the two objectives do not necessarily need to be considered at the decision making stage when the single-objective approach is used, these trade-offs still need to be dealt with at some stage, in this case, the carbon pricing stage. However, at the carbon pricing stage, consideration of the trade-offs between the two objectives is implicit. Therefore, as mentioned above, information about the actual trade-offs between the two objectives is lost. Thirdly, whether or not the carbon price (either determined by evaluation methods or by the carbon market) can present a fair resolution among all stakeholders is uncertain. Also, it is uncertain how accurately the carbon price can reflect the actual cost of carbon, especially if the carbon price is determined by the market only. These uncertainties can be passed to the WDS design process by using a single-objective approach. Fourthly, the single-objective approach is based on the assumption of perfect substitutability, in which one dollar worth of damage caused by GHG emissions can be compensated by a dollar worth of economic growth (Sterner and Persson 2007). However, perfect substitutability in mitigating global warming is not widely accepted. Many proponents of sustainability

believe that the damage to future global environmental systems due to global warming cannot be compensated by higher material richness of future generations (Neumayer 1999). Based on this belief, the environmental objective of minimizing GHG emissions should be optimized independently from system costs by employing a multi-objective optimization approach.

Finally, the single-objective approach of incorporating GHG emission minimization into the optimization of WDSs corresponds to the weighted sum method of solving multi-objective optimization problems (Deb 2002). Therefore, by repeating the single-objective optimization with different carbon prices, various multi-objective optimal solutions can be identified. However, it is often difficult to determine the appropriate weights for multi-objective function values in the weighted sum method, which is equivalent to the carbon prices in the single-objective approach in this study, so that a satisfactory spread of multi-objective optimal solutions along the Pareto-optimal front is obtained (Das and Dennis 1997; Deb 2002). It has also been proven that not all multi-objective optimal solutions can be found by using the weighted sum method (Miettinen 1999).

Since the carbon price has no impact on the relative ranking of the multi-objective optimal solutions, the multi-objective optimization formulation presented in this paper can be easily converted into a multi-objective optimization problem in which the system cost in dollars and GHG emissions in tonnes of CO₂-e are minimized. The single-objective approach proposed in this paper is closely related to this multi-objective approach by using a carbon cost mapping of the optimal solution space, as shown in

Figures 5 and 8. This carbon cost mapping of the optimal solution space obtained by using the multi-objective approach provides decision makers with a clear indication of the relative effectiveness of their selected carbon price in reducing GHG emissions relative to other carbon prices.

Summary and Conclusions

In this paper, the issue of how to optimize water distribution systems (WDSs) under an emissions trading scheme with a cap and trade approach is investigated by considering carbon pricing. There exist two ways to incorporate the minimization of GHG emissions into the optimization of WDSs based on a price of carbon: either a single-objective approach or a multi-objective approach. In the single-objective approach, the total cost, which is the sum of the system cost and the costs from GHG emissions based on a price of carbon, is optimized as the sole objective. In the multi-objective approach, the conventional objective of minimizing system cost and the second objective of minimizing GHG emissions via a price of carbon are optimized independently. Two case studies have been used to investigate the relationship between the two approaches. For each case study, two demand loading cases based on the peak day and average day with a 48-hour extended period simulation, and two different pipe roughness values over time were used to estimate the average energy consumption of the system due to pumping. In addition, four future possible carbon prices ranging from \$10 to \$120 per tonne of CO₂-e have been used to investigate the impact of market carbon prices on the optimization results.

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

In conclusion, considering the comparison of the single-objective and multi-objective approaches, a multi-objective approach considering system cost in dollars and GHG emissions in tonnes is recommended for the optimization of WDSs accounting for GHG

emissions, even under an emissions trading scheme with a cap and trade approach where the GHG emissions can be traded based on a carbon price.

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Figure 1 Objective function evaluation

Figure 2 Diurnal water demand curve (adapted from Hydraulic Computer Programming Pty. Ltd (1985))

Figure 3 Network configuration for case study 1 (tank 2 is the storage tank; the elevation at tank 2 refers to the initial tank water level)

Figure 4 Optimization results of case study 1 (the unfilled symbol represents the single-objective optimization solution obtained using the corresponding carbon price; and the network configurations corresponding to the design numbers are shown in Table 4)

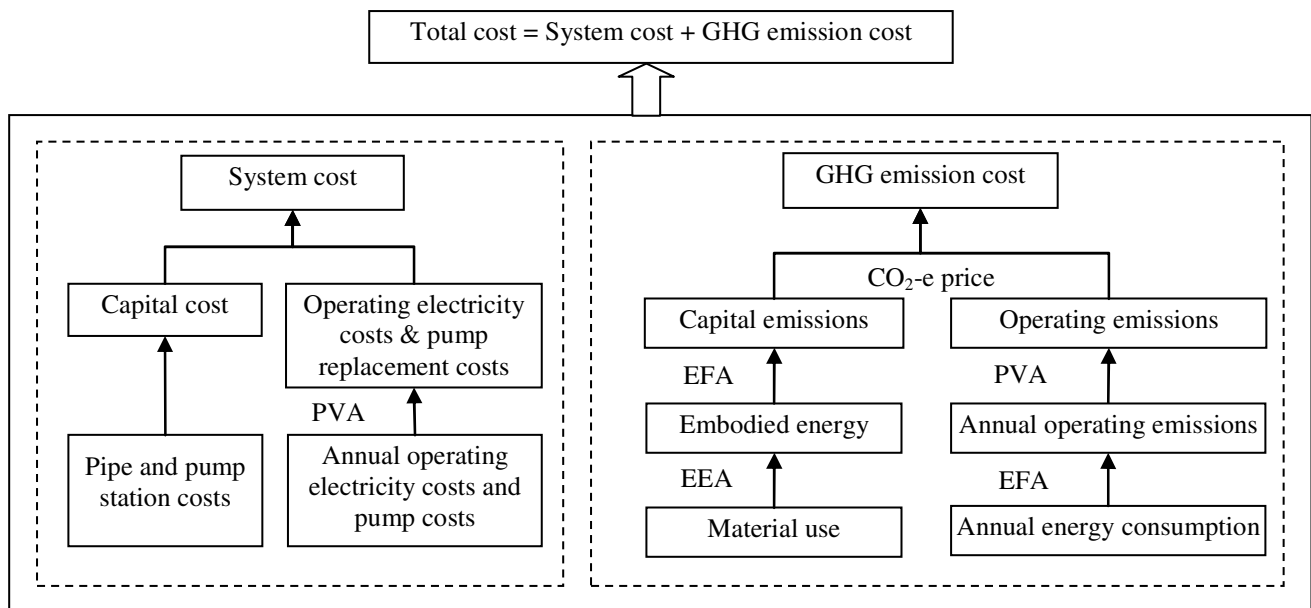
Figure 5 Carbon cost mapping of the optimal solution space of case study 1

Figure 6 Network configuration for case study 2 (tanks 7, 8 and 9 are storage tanks; the elevations at tanks 7, 8 and 9 refer to the initial tank water level)

Figure 7 Optimization results of case study 2 (the unfilled symbol represents the single-objective optimization solution obtained using the corresponding carbon price; and the network configurations corresponding to the design numbers are shown in Tables 6 and

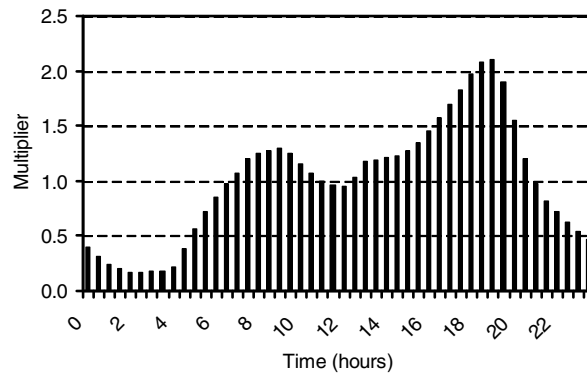
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Figure 8 Carbon cost mapping of the optimal solution space of case study 2

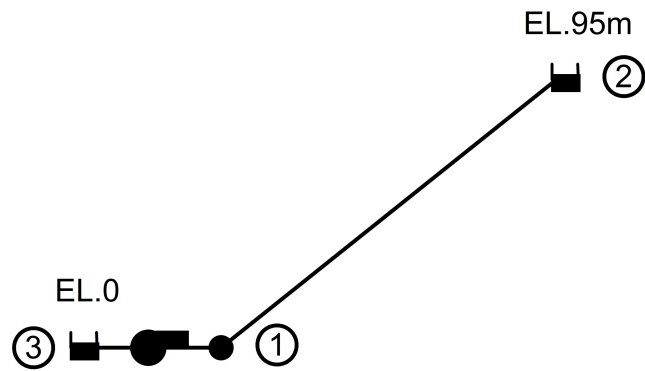


Note: PVA = present value analysis; EFA = emission factor analysis; EEA = embodied energy analysis

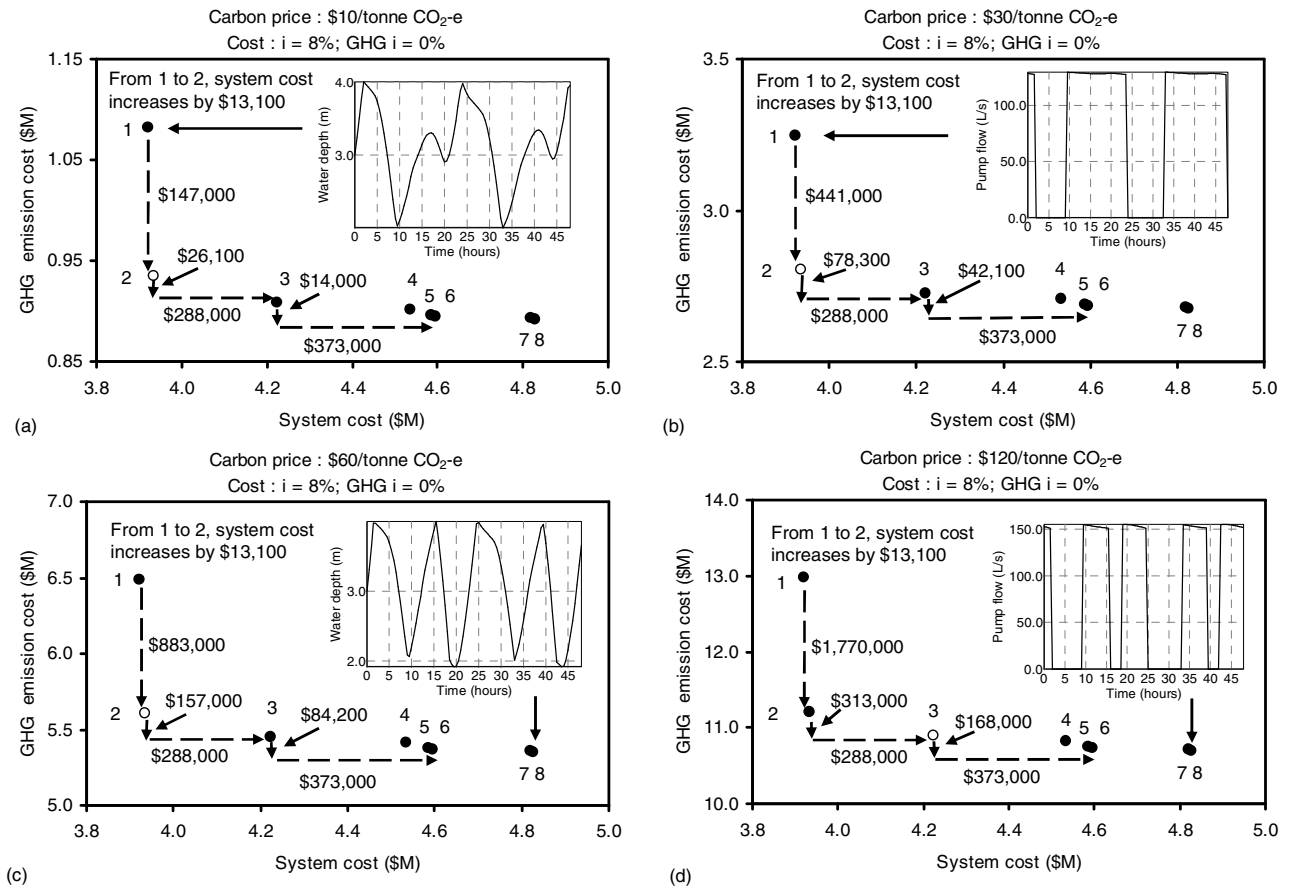
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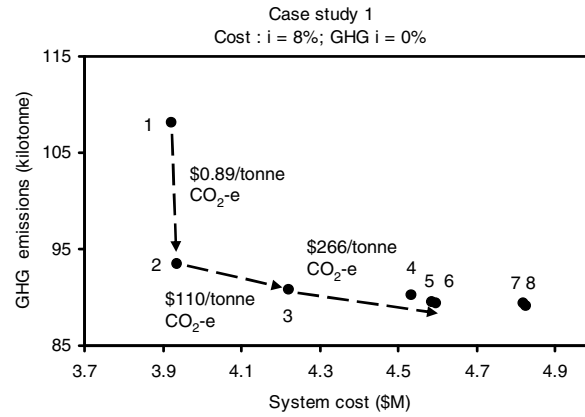
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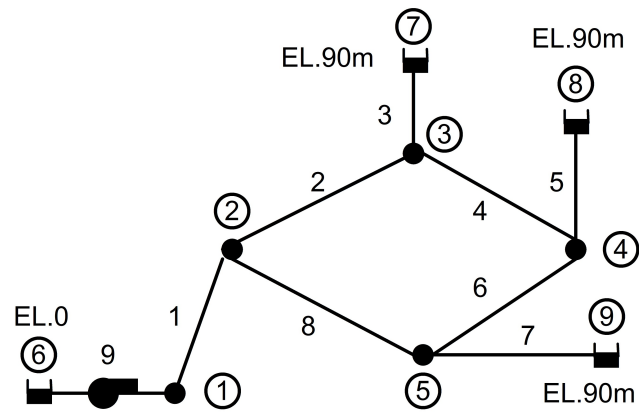
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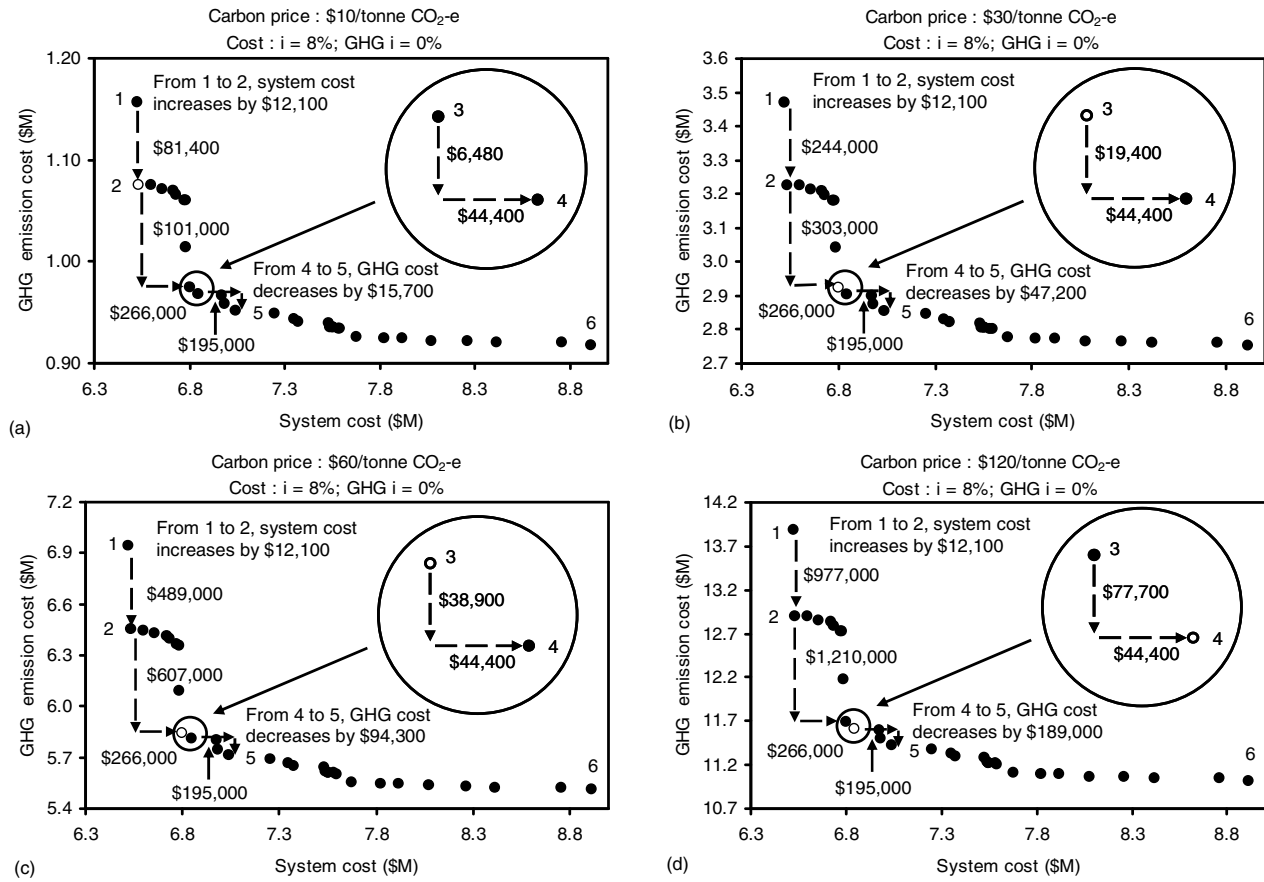
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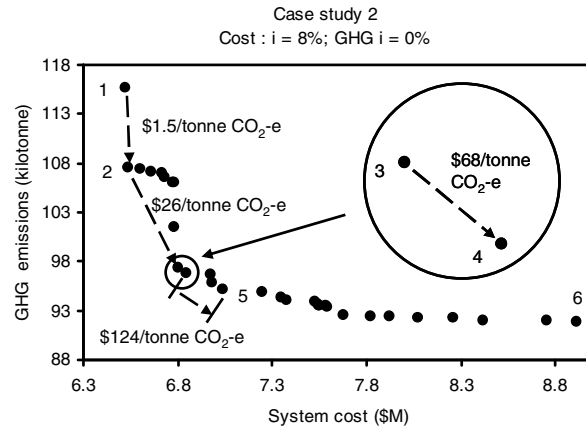
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Table 1 Design conditions of case study 1

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

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Table 2 Pump information (adapted from: Thompson Kelly & Lewis (2001))

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
5A	6LG13/A	2900	311	80	109	117	155	975	633
5B	6LG13/A	2900	321	81	113	125	171	1,039	684
6A	430DMH-4s	1480	275	84	157	94.6	173	1,047	690
6B	430DMH-4s	1480	312	85	180	121	251	1,320	926
7A	430DMH-5s	1480	251	84	142	99.2	164	1,011	662
7B	430DMH-5s	1480	312	85	180	151	313	1,502	1,097
8A	430DML-5s	1480	290	82	131	101	159	989	644
8B	430DML-5s	1480	313	82	140	118	197	1,138	767
9A	430DML-6s	1480	272	81	123	107	158	988	643
9B	430DML-6s	1480	313	82	140	142	238	1,277	888
12A	460DKL-4s	1480	295	84	162	90.7	171	1,038	683

*BEP: Best efficiency point; ** All costs in the case studies are in Australian dollars unless noted otherwise.

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Table 3 Ductile Iron Cement Mortar Lined (DICL) pipe information

No.	Dia. (mm)	Unit Cost (\$/m)	Unit Mass (kg/m)	No.	Dia. (mm)	Unit Cost (\$/m)	Unit Mass (kg/m)
1	100	228	18	14	900	2,012	310
2	150	307	30	15	960	2,040	337
3	225	433	51	16	1,000	2,142	356
4	300	568	74	17	1,050	2,270	379
5	375	813	99	18	1,085	2,360	396
6	450	1,033	126	19	1,220	2,655	461
7	525	1,252	154	20	1,290	2,860	496
8	600	1,415	183	21	1,350	2,996	526
9	675	1,658	213	22	1,500	3,337	603
10	700	1,739	223	23	1,650	3,678	683
11	750	1,900	244	24	1,800	4,020	765
12	800	1,950	266	25	1,950	4,361	849
13	825	1,976	277	26	2,100	4,696	935

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Table 4 Pareto-optimal solutions found for case study 1 (Cost: $i=8\%$; GHG $i=0\%$)

Design No.	Pump No.	Pipe Dia. (mm)	Pipe Cost (M\$)	Pipe GHG (kilotonnes)	Average Annual Energy Over First 50 Years (10^3 kWh)	Average Annual Energy Over Second 50 Years (10^3 kWh)	Total GHG Over 100 Years (kilotonnes)
1	1B	300	0.85	1.29	999	1,052	108.2
2	3A	375	1.22	1.73	871	890	93.4
3	3A	450	1.55	2.19	847	854	90.8
4	3A	525	1.88	2.68	838	841	90.2
5	12A	525	1.88	2.68	831	837	89.6
6	6A	525	1.88	2.68	830	835	89.4
7	12A	600	2.12	3.19	825	828	89.3
8	6A	600	2.12	3.19	823	826	89.1

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Table 5 Design conditions of case study 2

Total annual demand (m ³)	2,522,880
Average peak-day flow for each tank (L/s)	40
Pipe 1 length (m)	1,000
Pipe 2 length (m)	1,200
Pipe 3 length (m)	500
Pipe 4 length (m)	1,000
Pipe 5 length (m)	500
Pipe 6 length (m)	1,000
Pipe 7 length (m)	500
Pipe 8 length (m)	1,500

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Table 6 Selected optimal solutions found for case study 2 (Cost: $i=8\%$; GHG $i=0\%$)

Design No	Pump No.	Pipe 1 Dia. (mm)	Pipe 2 Dia. (mm)	Pipe 3 Dia. (mm)	Pipe 4 Dia. (mm)	Pipe 5 Dia. (mm)	Pipe 6 Dia. (mm)	Pipe 7 Dia. (mm)	Pipe 8 Dia. (mm)
1	8B	300	300	225	300	225	100	225	225
2	1B	375	300	225	225	300	100	225	225
3	3A	375	375	225	225	300	150	225	300
4	3A	375	375	225	300	300	100	225	300
5	3A	450	375	225	300	300	100	225	300
6	12A	600	525	375	375	375	100	300	375

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Table 7 Costs and GHG emissions of selected optimal solutions for case study 2 (Cost:

$i=8\%$; GHG $i=0\%$)

Design No.	Pipe Cost (M\$)	Pipe GHG (kilotonnes)	Average Annual Energy Over First 50 Years (10^3 kWh)	Average Annual Energy Over Second 50 Years (10^3 kWh)	Total GHG Over 100 Years (kilotonnes)
1	3.34	4.74	1,023	1,106	115.7
2	3.52	4.90	968	1,002	107.5
3	4.10	5.79	864	895	97.4
4	4.15	5.92	858	886	96.8
5	4.37	6.23	844	864	95.2
6	6.27	8.94	792	799	91.8

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