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Scenario Driven Optimal Sequencing under Deep Uncertainty

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Abstract

The optimal sequencing / scheduling of activities is vital in many areas of environmental and water resources planning and management. In order to account for deep uncertainty surrounding future conditions, a new optimal scheduling approach is introduced in this paper, which consists of three stages. Firstly, a portfolio of diverse sequences that are optimal under a range of plausible future conditions is generated. Next, global sensitivity analysis is used to assess the robustness of these sequences and to determine the relative contribution of future uncertain variables to this robustness. Finally, an optimal sequence is selected for implementation. The approach is applied to the optimal sequencing of additional potential water supply sources, such as desalinated-, storm- and rain-water, for the southern Adelaide water supply system, over a 40 year planning horizon at 10-year intervals. The results indicate that the proposed approach is useful in identifying optimal sequences under deep uncertainty.

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1 INTRODUCTION

The sequencing, staging or scheduling of activities (referred to as sequencing for the remainder of this paper) is important in many environmental and water resources application areas. Examples include the sequencing of urban water supply augmentation sources and infrastructure (Beh et al., 2014; Kang and Lansey, 2014; Mortazavi-Naeini et al., 2014; Ray et al., 2013), the scheduling of pumps and rehabilitation activities in water distribution systems (Kleiner et al., 1998; Dandy and Engelhardt, 2001; Dandy and Engelhardt, 2006; Savić et al., 2011; Zheng and Zecchin, 2014), the scheduling of wastewater discharges (Murillo et al., 2011), the scheduling of mining production activities (Badiozamani and Askari-Nasab, 2014), the scheduling of forest management activities (Sharples et al., 2009; Simon and Etienne, 2010; Zhang and Barten, 2009), the scheduling of irrigation water (Ge et al., 2013; Merot and Bergez, 2010), the scheduling of crop management activities (Lautenbach et al., 2013; Ripoche et al., 2011), the scheduling of environmental flows in rivers (Szemis et al., 2013; Szemis et al., 2012) and determining the optimal schedule of investments of conservation funding (Bode et al., 2008; Wilson et al., 2006).

In order to make best use of available resources and to achieve the best possible outcomes, the use of formal optimisation techniques is highly desirable in order to identify these sequences. However, a potential problem with the use of formal optimisation methods is that solutions are only truly optimal if the assumptions under which the optimisation was performed hold. This is unlikely to be the case for real systems (Dessai et al., 2013; Gober, 2013), therefore necessitating the consideration of uncertainties as part of optimisation approaches (Maier et al., 2014). The uncertainties underpinning optimisation approaches generally fall into two categories: those resulting from a lack of information and those resulting from uncertainties about the future (which is referred to as deep uncertainty) (Walker et al., 2013). The latter type of uncertainty can also be thought of as global uncertainty, which results in significantly different trends in solutions, whereas the former type of uncertainty can be thought of as local uncertainty, which represents the imperfect knowledge surrounding a particular pathway resulting from global uncertainties (Mejia-Giraldo and McCalley, 2014).

Local uncertainty, or a lack of information, can generally be represented by probability distributions and there are well-established methods for dealing with this type of uncertainty within optimisation frameworks for optimal sequencing (e.g. Bode et al., 2008; Srinivasa Prasad et al., 2013; Wilson et al., 2006). In contrast, optimisation methods for dealing with optimal sequencing under global /

deep uncertainty are much less developed. This is despite the fact that it has been recognised that most important strategic planning problems are characterised by deep uncertainty (Walker et al., 2013). In general, two of the most promising approaches to dealing with deep uncertainty include the development of robust solutions, which are designed to perform well under a wide range of future conditions, and the development of flexible solutions, which are designed to enable adaptation to changing future conditions (Walker et al., 2013). In the context of optimal sequencing, Woodward et al. (2014) and Basupi and Kapelan (2013) developed flexible approaches to the optimal sequencing of flood risk management and water distribution system design, respectively. However, in each case only a relatively limited range of reasonably well-known future conditions was considered (represented by probability distributions), rather than alternative scenarios, as is generally the case when dealing with deep uncertainty. As pointed out by Mahmoud et al. (2009), probabilistic predictions explicitly weight the likelihood of different outcomes, whereas scenarios are designed to represent a set of alternative plausible future states of the world. In addition, the approaches of Woodward et al. (2014) and Basupi and Kapelan (2013) were tailored to specific application areas.

Housh et al. (2013), Kang and Lansey (2014) and Ray et al. (2012) developed optimal sequencing approaches for water supply system management, water supply infrastructure and water sources, respectively, that consider performance under a wide range of future conditions with the aid of scenarios. However, all of these approaches are tailored to specific application areas. In addition, the methods proposed by Housh et al. (2013) and Ray et al. (2012) are based on traditional optimisation methods (i.e. stochastic and linear programming, respectively, in this case), which have a number of potential disadvantages compared with evolutionary optimisation approaches (see Maier et al., 2014). These include not being able to be linked with simulation models, thereby potentially ignoring important non-linear interactions and making the algorithms more difficult to apply, and not being truly multi-objective in the sense of being able to evolve fronts of Pareto-optimal solutions (Pareto, 1896) in a single optimisation run, which is becoming increasingly important when tackling real-life problems (Maier et al., 2014). Although Kang and Lansey (2014) use a genetic algorithm as their optimisation engine and indicate that their approach could be extended to include multiple objectives, this was not undertaken in their paper.

In order to address the shortcomings outlined above, the objectives of this paper are (i) to introduce an approach to the optimal sequencing of environmental and water resources activities that (a) is generic, (b) caters to a wide range of possible future conditions and (c) caters to multiple objectives; and (ii) to illustrate the approach on an optimal urban water resources augmentation case study, which is based on the southern water supply system of Adelaide, South Australia.

The remainder of this paper is organised as follows. In Section 2, the proposed optimal sequencing approach under deep uncertainty is introduced, while details of the case study and of the application of the proposed approach to the case study are given in Section 3. The results are presented in Section 0, before a summary and conclusions are given in Section 5.

2 PROPOSED APPROACH

As illustrated in Figure 1, the proposed approach to the optimal sequencing of environmental and water resources activities under deep uncertainty consists of three main steps, namely (i) the identification of a portfolio of diverse optimal sequences; (ii) the performance of global sensitivity analysis on each of the members of the portfolio of optimal sequences identified in (i); and (iii) the selection of the optimal sequence to be implemented. Details of each of these steps are given in the following subsections. It should be noted that the proposed approach assumes that the optimisation problem to be solved has already been formulated (e.g. identification of objectives, constraints and decision variables, planning horizon and interval etc.). As with all optimisation problems, problem formulation is vital and care needs to be taken to ensure the concerns of decision makers and other stakeholders are represented in the problem formulation (see Maier et al., 2014).

2.1 Determination of Portfolio of Diverse Optimal Sequences

In line with robust decision-making approaches (Lempert and Collins, 2007; Matrosov et al., 2013a), the purpose of the first step in the proposed approach is to identify a portfolio of diverse solutions that are likely to perform differently under various future conditions. This is also in keeping with the philosophy underpinning scenario analysis, in which scenarios "provide a dynamic view of the future by exploring various trajectories of change that lead to a broadening range of plausible alternative futures" (Mahmoud et al., 2009), enabling "…a creative and flexible approach to preparing for an uncertain future" (Mahmoud et al., 2009). As shown in Figure 1, in order to achieve this, three steps are proposed in the context of developing optimal sequences under deep uncertainty. The first of these involves the identification of the uncertain variables (UV_1, UV_2,...,UV_x) that are likely to result in unknown futures of interest (Step 1.1, Figure 1), as well as their plausible ranges over the selected planning horizon (e.g. $UV_{x,min}$,$UV_{x,max}$). For example, these variables could include population, land use, precipitation, temperature, evapotranspiration, water availability etc., depending on the environmental / water resources problem under consideration.

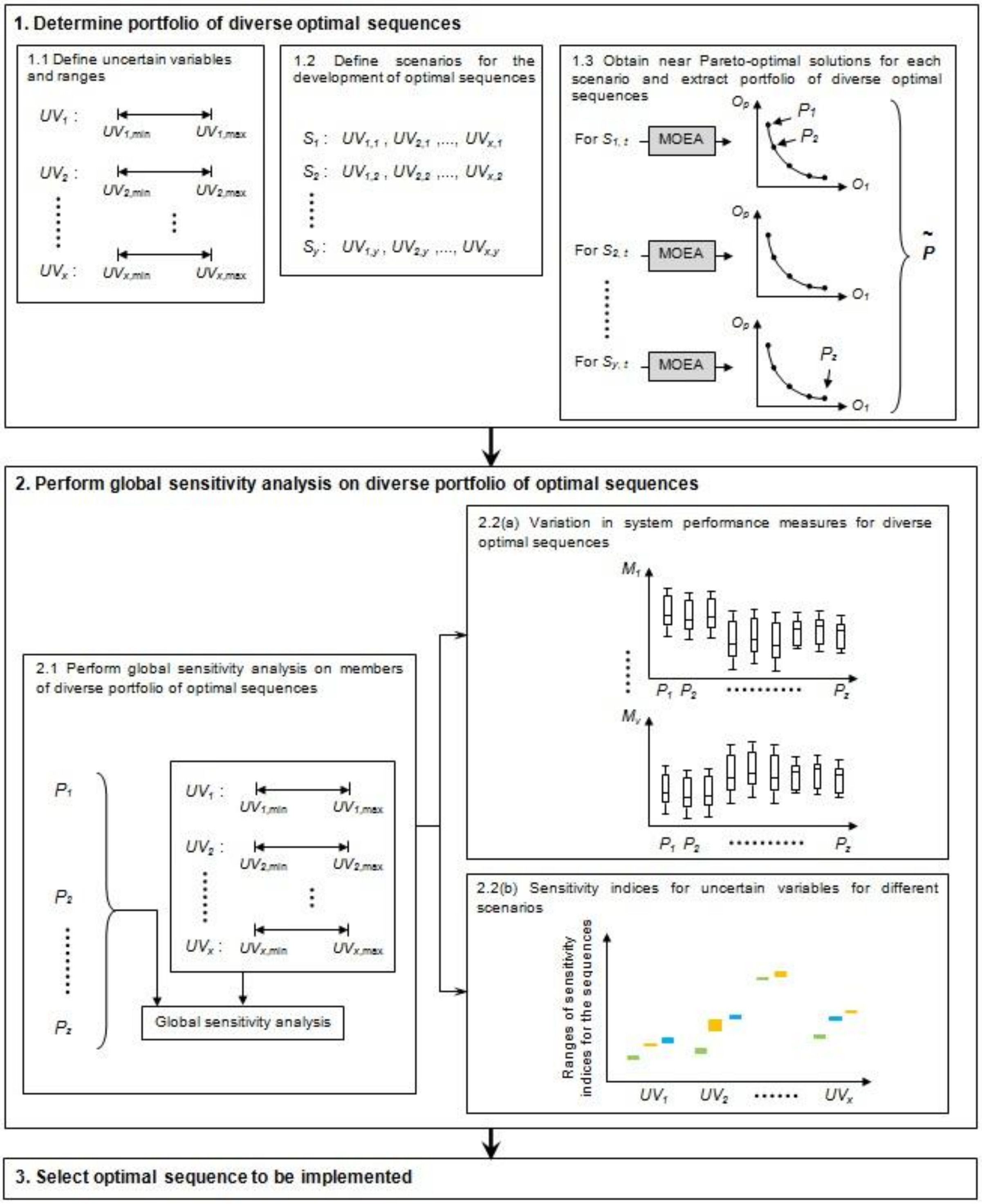

Figure 1 Schematic of proposed scenario driven optimal sequencing of environmental and water resource activities under deep uncertainty

Next, a set of plausible future scenarios (S_1, S_2, ...,S_y), which consist of different combinations of values of the selected uncertain variables, as well as their temporal variation over the selected planning horizon, should be selected (Step 1.2, Figure 1). The purpose of the scenarios is not to predict the future, but to enable exploration of a relatively small number of different plausible futures that are generally not equally likely (Mahmoud et al., 2009). Most scenario development involves people from different disciplines and organisations (Mahmoud et al., 2009) and can be achieved using a range of formal (Leenhardt et al., 2012; Mahmoud et al., 2009) or informal approaches (e.g. Kasprzyk et al., 2012; Paton et al., 2014a; Paton et al., 2013; Paton et al., 2014b).

The final step involves the generation of Pareto-optimal sequences for each of the scenarios and the extraction of the portfolio of diverse solutions (P_1, P_2 to P_Z) (Step 1.3, Figure 1), which is similar to the approach used by Kasprzyk et al. (2013) for problems that do not involve sequencing. The philosophy underpinning this step is to identify potential future pathways that are optimal with respect to the stated objectives under the conditions represented by the different scenarios (i.e. plausible futures). It should be noted that when dealing with multiple, competing objectives, there is no single optimal solution, but a collection of solutions that are all optimal, known as the Pareto front (Pareto, 1896). This is because for solutions on this front, improvements in one objective can only be achieved at the expense of degradation in at least one of the other objectives, requiring additional preference information to enable one of these solutions to be selected (Cohen and Marks, 1975). Consequently, the purpose of the proposed approach is not to identify a single optimal solution, but to sift through the large number of potential solutions in order to identify the solutions that provide the best possible trade-offs between objectives under a number of different future scenarios and therefore warrant further consideration by decision-makers.

Although a variety of approaches can be used to generate the front of (near) Pareto-optimal solutions, the use of multi-objective evolutionary algorithms (MOEAs), such as NSGAII (Deb et al., 2002) or BORG (Reed et al., 2013), is recommended, as they can identify the front of (near) Pareto optimal solutions in a single optimisation run and can be linked with existing simulation models. However, the most appropriate approach is likely to be application and case study dependent. When deciding which solutions on the *y* Pareto fronts to include in the portfolio of diverse sequences (P_1, $P_2$to P_Z) to be subjected to the sensitivity analysis step, the aim is to obtain diversity in both the decision and objective function spaces. Depending on the characteristics of the problem considered (e.g. number of objectives, number of scenarios, number of diverse solutions), there might be some benefit in using formal approaches, such as visual analytics (see e.g. Kollat and Reed, 2007; Reed and Kollat, 2013) or scenario discovery (e.g. Kasprzyk et al., 2013; Lempert and Groves, 2010), to assist with this process.

2.2 Global Sensitivity Analysis

Global sensitivity analysis can be conducted using a number of methods, such as Sobol' (Sobol', 1990) or Fast (Saltelli and Bolado, 1998), among others. The purpose of the global sensitivity analysis step of the proposed approach (Step 2.1, Figure 1) is: (i) to assess how well each of the members of the diverse portfolio of optimal sequences (i.e. the sequences that provide the optimal trade-offs between the objectives under different plausible future conditions) selected in Step 1 (P_1, $P_2$to P_Z) performs under the full range of selected uncertain future conditions ($UV_{1, min}$ to $UV_{1, max}$; $UV_{2, min}$ to $UV_{2, max}$; …; $UV_{x, min}$ to $UV_{x, max}$) in accordance with a number of user defined performance measures (M_1, M_2, … ,M_y) (Step 2.2(a), Figure 1); and (ii) to identify the relative contribution of the different uncertain variables (UV_1, UV_2, … ,UV_x) to the variation in the performance of the different optimal sequences (P_1, $P_2$to P_Z) (Step 2.2(b), Figure 1). The former provides an indication of the insensitivity (and hence robustness) of each of the selected optimal sequences to different plausible futures, enabling the impact of deep uncertainty on the performance of different optimal sequences to be explored and assessed. The latter provides an indication of the degree to which the variation in performance under different combinations of future conditions is within the control of the authority in charge of the system under consideration. For example, in the context of urban water supply augmentation, if the largest cause of the variation in future performance is climate change, the water authority in charge would have little control over this and might need to be more conservative in the selection of the most appropriate optimal sequence (e.g. select a sequence that performs well under a wider range of future conditions). In contrast, if the major cause of variation in performance is per capita demand, which can, to some extent be influenced by the water authority, a less conservative optimal sequence could be selected. It also gives an idea of where the water authority should focus its efforts if it wishes to reduce future uncertainty.

The selected performance measures (M_1, M_2, …,M_y) would generally include, but not necessarily be restricted to, the optimisation objectives. For example, if the problem to be optimised includes one or more constraints that signify acceptable system performance (e.g. supply meeting demand in the case of urban water supply augmentation), additional performance measures could relate to the satisfaction of these constraints under the uncertain future conditions considered (e.g. in the case of urban water supply augmentation, such measures could include reliability, resilience and vulnerability, as recommended by Yazdani et al. (2011), or the risk of water shortages, as suggested by Hall et al. (2012)).

In order to account for *variability* in system states (rather than *trends* over time) (see Mortazavi et al., 2012), the global sensitivity analyses might need to be repeated a number of times for each of the optimal sequences considered. For example, in the case of urban water supply augmentation, available water supply from rainfall dependent sources would vary from year to year based on natural rainfall variability. In this case, the global sensitivity analysis should be repeated for different stochastically generated rainfall time series and the variation in system performance (Step 2.2(a), Figure 1) and sensitivity indices (Step 2.2(b), Figure 1) would be averaged over the sensitivity analyses for each of the stochastic series.

2.3 Selection of Optimal Sequence

The previous steps identify sequences that provide optimal trade-offs between objectives under different plausible future pathways, as well as the sensitivity of these solutions to possible changes in future conditions. However, as all of these solutions are optimal with respect to different objectives and scenarios, user preferences have to be used to determine which sequence to adopt. Consequently, as stated previously, the proposed approach does not suggest which solution should be adopted, but provides decision-makers with the best set solutions that consider further consideration. Factors that should be considered in this decision-making process include:

- Trade-offs between the absolute (e.g. average) values of the performance measures and their variability (Step 2.2(a), Figure 1) (see Cui and Kuczera, 2010).
- The relative contribution of the uncertain variables to variability in performance (Step 2.2(b), Figure 1) and how easily this can be managed.
- The degree to which various constraint violations resulting from uncertain future conditions can be managed.
- The degree of adaptability associated with different optimal sequences. As decisions associated with optimal sequences are not implemented at the same time, there is scope to make changes to the optimal sequence in light of updated information. Consequently, optimal sequences for which decisions at the earliest stages of the planning horizon are the same afford greater adaptability than sequences for which optimal decisions at the earliest

stages are different. However, it should be noted that adaptive pathways (see Haasnoot et al., 2014) are not formally considered in the proposed approach.

Depending on the complexity of the problem, this decision-making process can be undertaken informally or using more formal approaches, such as multi-criteria decision analysis (see Hyde and Maier, 2006; Korteling et al., 2013).

3 Case Study

3.1 Introduction

In order to illustrate and test the utility of the proposed approach, it is applied to an urban water supply augmentation case study based on the southern region of the Adelaide water supply system in 2010. While deep uncertainty has been considered in urban water resources planning previously (e.g. Kang and Lansey, 2013; Korteling et al., 2013; Lempert and Groves, 2010; Maier et al., 2013; Matrosov et al., 2013a; Matrosov et al., 2013b; Paton et al., 2014a; Sahin et al., 2014), only some studies have considered the use of formal optimisation approaches (e.g. Kasprzyk et al., 2013; Kasprzyk et al., 2012; Kasprzyk et al., 2009; Paton et al., 2014b; Wang and Huang, 2014; Zeff et al., 2014) and only Ray et al. (2012) have considered the optimal *sequencing* of water supply augmentation options.

Adelaide is the capital city of South Australia (see Figure 2) and has an estimated population of approximately 1.3 million. It is one of the driest capital cities in the world (Wittholz et al., 2008), having a Mediterranean climate, with hot dry summers and mild wet winters. The recorded annual rainfall ranges from 257mm to 882mm (Maier et al., 2013). Average annual mains water consumption was estimated to be 163 gigalitres (GL) in 2008 (Government of South Australia, 2009), but the demand varies by +/- 12% depending on the prevailing weather patterns (Government of South Australia, 2005).

The southern Adelaide water supply system (WSS) (see Figure 2) supplies around 50% of the demand of metropolitan Adelaide. In 2010, the system was supplied with water from three reservoirs – Myponga, Mount Bold and Happy Valley. Mount Bold and Myponga reservoirs receive water from local catchments, and Mount Bold also receives water pumped from the River Murray via the Murray Bridge to Onkaparinga pipeline. The amount of water supplied to Adelaide from the River Murray is based on a licence to supply a maximum of 650 GL over a 5-year rolling period. Of this, half is assumed to be allocated to the southern Adelaide WSS. The Happy Valley reservoir is a service reservoir, which stores water transferred from Mount Bold reservoir prior to treatment at the Happy Valley water treatment plant.

In order to cater to projected demand increases and the impacts of climate change, there are plans to augment Adelaide's future water supply (Beh et al., 2014; Paton et al., 2013, 2014b). Potential water supply augmentation sources include a desalination plant at Port Stanvac, various stormwater harvesting schemes, and household rainwater tanks, as detailed in Beh et al. (2014) and Paton et al. (2014b). Consequently, the optimisation problem to be solved involves the sequencing of the potential supply augmentation options over a given planning horizon (see Beh et al., 2014). This problem is used here for illustration purposes of the proposed approach, as it has been studied previously in relation to the identification of optimal water supply augmentation options (Paton et al., 2013, 2014a, 2014b), as well as the optimal sequencing of these options without the consideration of uncertainty (Beh at al., 2014). A description of this problem, as well as how the proposed approach was applied to it, is given in the following sections. However, as this problem has been studied previously, details that are presented in other papers are only summarised here for the sake of brevity.

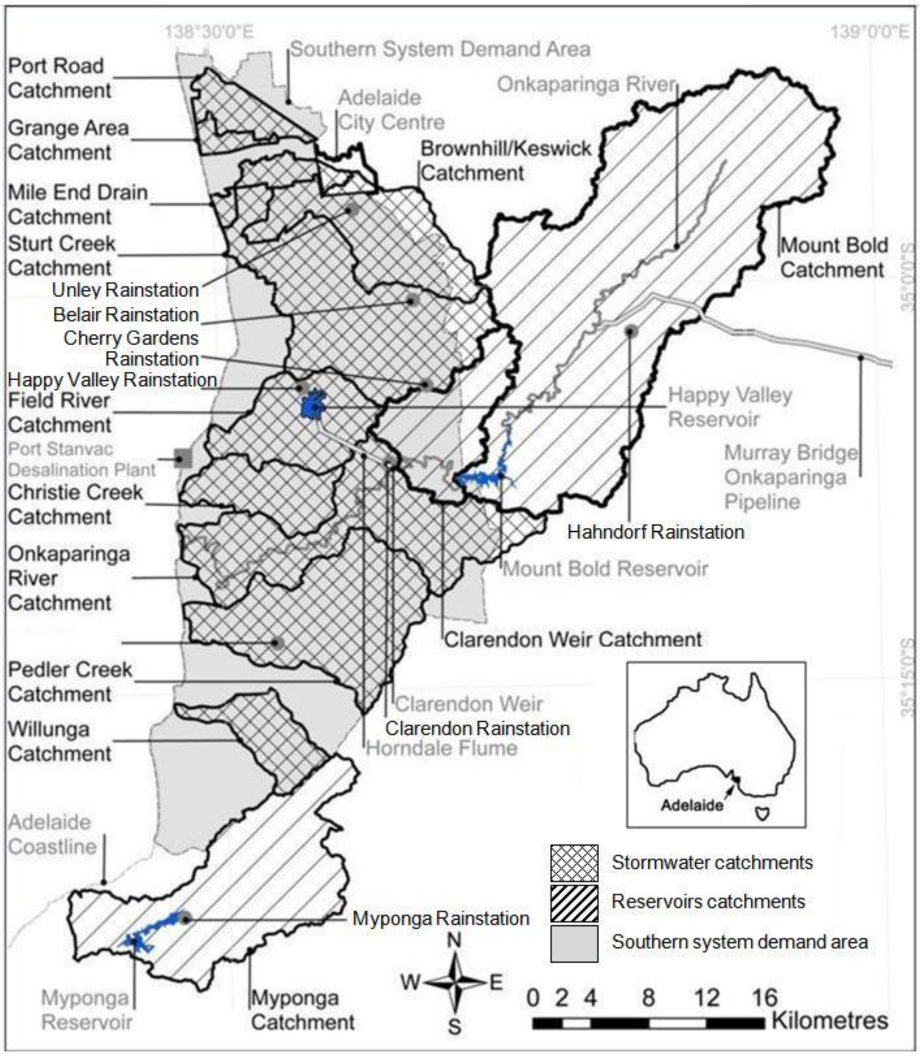

Figure 2 Map of the Southern Adelaide water supply system (WSS) and potential augmentation options in 2010.

3.2 Problem formulation

3.2.1 Objectives and Constraints

The objectives to be optimised include the minimisation of the present value (PV) of cost and the present value of GHG emissions. Both objectives consist of two components, including capital and operating values. As these objectives are generally in competition with each other (see Wu et al., 201a, b; 2013), there will not be a single optimal solution, but fronts of Pareto-optimal solutions, as discussed in Section 2.1. The discount rates used for the calculation of the PV of cost and GHG emissions are considered to be uncertain variables (see Section 3.3.1). The primary constraint is that supply capacity is greater than or equal to demand at all times.

3.2.2 Decision Variables

The existing water supply options (i.e. the three reservoirs and supply from the River Murray) are included in the sequence plan at the beginning of the planning horizon. However, the desalination plant, stormwater harvesting schemes and household rainwater tanks are considered as potential additional water supply sources at each decision stage. It should be noted that the nominal capacity of the desalination plant is halved for the case study because it is designed to supply the whole of metropolitan Adelaide. The southern system featured in the case study, therefore, only takes 50% of the supply.

A 40- year planning horizon and a ten year staging interval are adopted. A staging interval of ten years allows for periodic review of the plans due to changing exogenous variables, such as rainfall, demand and energy costs. Ten years is also a practical period, as it allows time for planning, design, approval and construction of projects. Therefore, the case study includes five decision stages over the 40 year planning horizon. A complete sequence plan consists of the selected options at each decision stage, in addition to the existing water supply system.

Details of the current and potential future water supply sources, including their estimated yields and capital and operating costs and GHG emissions, are summarised in Table 1 (see Beh et al., 2014). It should be noted that while the yields of the rainfall independent sources are known, the yields of the rainfall dependent sources are estimates obtained by simulating each source individually under a range of hydrological conditions and projected demands, as outlined by Beh et al. (2014). Similarly, whereas the capital costs and GHG emissions are fixed, their corresponding operational values vary over time. Consequently, the unit values in Table 1 are estimates. However, during the optimisation process, time-varying values of yields, operational costs and operational GHG emissions are obtained with the aid of a simulation model, as discussed in Section 3.2.3.

Although a minimum estimated reliability of 90% is used for the rainfall dependent sources, actual system reliability is higher than this as supply capacity actually exceeds system demand most of the time. Furthermore the reliability of the desalination plant is determined by mechanical and electrical breakdown and is much higher than 90%.

Table 1 Estimated yields, capital and unit operating costs and GHG emissions for the potential water supply options (see Beh et al., 2014)

Water supply options	Estimated yields (90% reliability)	Capital cost ($)	Unit operating cost ($/kL)	Capital GHG emissions* ($kgCO_2$-e)	Unit GHG emissions* ($kgCO_2$-e/kL)
River Murray	51.3 GL/year	-	0.49	-	3.33
Reservoirs:					
Happy Valley	50.3 GL/year	-	0.08	-	0.32
Myponga	6.4 GL/year	-	0.23	-	0.22
Stormwater harvesting schemes :					
Brownhill & Keswick Creek	6.3 GL/year	160,025,000	1.23	7,249,000	2.04
Sturt River	7.0 GL/year	194,193,000	1.23	7,351,000	2.06
Field River	1.6 GL/year	35,689,000	1.23	3,576,000	6.05
Pedler Creek	5.0 GL/year	110,682,000	1.23	5,643,000	1.60
Household rainwater tanks:					
1kL	35.0 kL/tank/year	2,181/tank	0.78	718/tank	1.22
2kL	42.8 kL/tank/year	2,464/tank	0.68	1,251/tank	1.22
5kL	46.8 kL/tank/year	3,024/tank	0.64	2,897/tank	1.22
10kL	47.1 kL/tank/year	3,560/tank	0.63	4,635/tank	1.22
	Actual yields				
50GL desalination plant	25.0 GL/year	1,347,000,000	1.00	228,538,000	5.41
50GL desalination expansion	25.0 GL/year	483,000,000	1.00	8,565,000	5.41

*Note that the GHG emissions given in this table are gross emissions. These may be partially or fully offset by the purchase of green energy or carbon offsets.

It should also be noted that not all of the water supply options in Table 1 are independent of each other. In particular: (i) Once one of the desalination options has been selected, it cannot be selected again. In addition, expansion to full capacity is only possible once the 50GL desalination plant has been selected; (ii) One or more of the stormwater harvesting schemes can be selected at any decision point. However, each scheme can only be selected once; and (iii) Rainwater tanks of a particular capacity can be implemented at any decision point. However, the option to use rainwater tanks as a source can only be selected once. In addition, it is assumed that once a particular rainwater tank capacity option has been selected, this is implemented across all dwellings as a result of government regulation.

3.2.3 Checking of Constraints and Calculation of Objectives

The checking of constraints involves determining whether the simulated capacity of the water supply system corresponding to a selected sequence plan is greater than or equal to the estimated demand at each decision stage and whether the generated combinations of options satisfy the feasibility criteria associated with the desalination plant (e.g. ensuring that the 50GL/year expansion only occurs after the implementation of the original 50GL/year plant). Calculation of the objectives involves determining the present value of capital and operational costs and GHG emissions for the water supply system corresponding to the selected sequence plan. Consequently, the development of a water supply system model for the selected sequences is required. In this study, *WaterCress* (Water - Community Resource Evaluation and Simulation System) is used for this purpose.

WaterCress is a water balance model that enables simulation of the real life layout as an assembly of components of a water supply system. Each component has an associated database that contains all variables (e.g. demand, rainfall, evaporation) necessary to enable quantities of water to be estimated and tracked through a specified water supply system (Clark et al., 2002). *WaterCress* is chosen for this case study because it (i) can incorporate multiple rainfall time series, (ii) can model multiple catchment-reservoir relationships, (iii) can incorporate less conventional water supply sources (e.g. desalination and recycled water), (iv) is freely available, (v) was developed specifically for South Australian conditions and (vi) has been used successfully for the case study system in previous studies (Beh et al., 2014; Paton et al., 2014b).

As the supply from the stormwater and rainwater sources is not potable, different sources have to be mapped to different end-uses in the model (e.g. Paton et al., 2014a). Specifically, potable supply is used for indoor residential use and the potable portion of the demand for industrial, commercial, primary production and public purposes (ICPP), rainwater is used for residential outdoor use and toilet flushing, and stormwater is used for the non-potable portion of the demand for ICPP. However, when the supply from stormwater harvesting and / or rainwater is insufficient to meet the designated demands, it is supplemented by potable supply from reservoirs and/or the desalination plant.

Total demand is a function of population size, per capita demand and commercial and industrial demand. Population is considered as one of the uncertain variables, as detailed in Section 3.3.1.

Average household size is assumed to be constant at 2.3 people over the planning horizon. This is because the average household size for SA is projected to decline from 2.6 (in 2006) to between 2.0 and 2.2 people per household by 2026 (Trewin, 2004). Per capita demands are held constant over the planning horizon at 491L/p/day based on 2010 values (Beh et al., 2014).

Hydrological inputs are based on continuous time series of rainfall and evaporation from 1910 to 2010, obtained for eight rainfall stations within the southern Adelaide WSS (Figure 2). However, these were adjusted for climate change and are thus considered as uncertain variables (see Section3.3.1). Further details of the *WaterCress* model are given in Beh et al. (2014) and Paton et al. (2014b).

3.3 Determination of Portfolio of Diverse Optimal Sequences

3.3.1 Definition of uncertain variables and ranges

As mentioned previously, three uncertain variables are considered, namely population, climate change (affecting rainfall and evaporation) and discount rate (for both cost and GHG emissions). Population and climate change are used as uncertain variables as they have been found to have the biggest impact on the water supply security constraint (i.e. that supply has to be greater than or equal to demand) for the case study system (Paton et al., 2013) and the discount rates are used as they are likely to have a significant impact on objective function values. Details of the uncertain variables are given in Table 2 and discussed below. As is generally the case in sensitivity analysis, all values within the ranges of the uncertain variables are considered equally likely (i.e. equivalent to assuming a uniform distribution for each).

Table 2 Uncertain variables and corresponding options

Uncertain variables	Options		
Population	Extremely high	(see Figure 3)	
	Very high		
	High		
	Moderate		
	Low		
	Very low		
	Extremely low		
Climate change impact		**GCMs**	**SRES**
	Most severe	CSIRO: CSIRO Mk3.5	A1B
	Very severe	NCAR: NCAR CCSM3	A1T
	Severe	CCR: MIROC-H	A1F1
	Moderate	LASG/IAP - FGOALS - G1.0	B2
	Less severe	MRI - CGCM 2.3.2	A1B
	Mild	CCR: MIROC-M	A2
	Least severe	CCCMA:CGCM3.1 (T63)	B1
Discount rate (for cost and GHG emissions)		**Cost**	**GHG emissions**
	High	8%	3%
	Moderate	6%	1.4%
	Low	4%	0%

Population

The population for the southern Adelaide region is estimated to be 600,240 in 2010 (Australia Bureau of Statistics, 2011) and seven series of annual population projections to 2050 are used as uncertain variables (see Figure 3). These projections are based on various assumptions of fertility, mortality, net interstate migration and net overseas migration (Australia Bureau of Statistics, 2013).

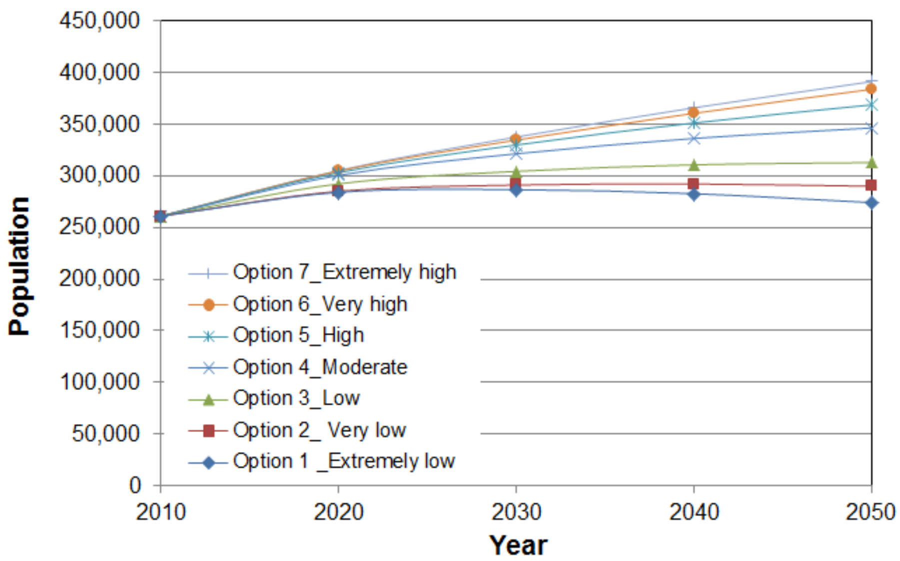

Figure 3 Uncertain time series of population growth consideredfor the southern Adelaide WSS to 2050 (Australia Bureau of Statistics, 2013).

Climate change

Future climate change will have an impact on the yield of rainfall dependent water supply sources (e.g. reservoirs, stormwater harvesting, rainwater tanks) and is considered via uncertainty in both SRES scenarios, representing potential carbon futures, and Global Circulation Models (GCMs), representing modelling uncertainty (see Table 2). As suggested by Paton et al. (2013) for the same case study area, the six SRES scenarios of A1FI, A1T, A2, B1 and B2 are used, as they cover the full range of potential future development pathways defined by the Intergovernmental Panel on Climate Change (IPCC) (Intergovernmental Panel on Climate Change, 2007). The seven GCMs considered include CCSM3, CGCM3.1, CSIRO-MK3.5, FGOALS-g1.0, MIROC3.2 (hires), MIROC3.2 (medres), and MRI-CGCM2.3.2 and are selected by applying CSIRO's Climate Future Framework (CFF) (see Paton et al., 2013). Based on the outputs of different combinations of SRES scenarios and GCMs, the climate change impacted rainfall and evaporation data are obtained by multiplying the 40 year series of historical daily rainfall and evaporation data by the climate change factors obtained from OzClim (http://www.csiro.au/ozclim/). These climate change factors are available at five-year intervals, so the percentage change factors are updated every five years from 2010 to 2050, as was done by Paton et al. (2013) for the case study area. The use of this constant scaling approach for the modelling of climate change effects was justified by Fowler et al (2007) and Paton et al (2014a).

Economic and GHG emission discount rate

The three economic discount rates used are: 4% per year (low), 6% per year (medium) and 8% per year (high), as a discount rate of 6% is commonly used by the local water authority and the Government of South Australia (2007) recommends that a +/-2% shift in the discount rate should be used in economic discount rate sensitivity analysis. In relation to GHG emission discount rates, suggestions include 0% per year, as in the Intergovernmental Panel on Climate Change's Second Assessment Report (Fearnside, 2002), 1.4% per year, which is considered appropriate for stabilizing GHG concentrations in the atmosphere within a desired range (Wu et al., 2010b) and values similar to those used for economic benefits and costs (Van Kooten et al., 1997). Consequently, GHG emission discount rate options of 0% per year (low), 1.4% per year (medium) and 3% per year (high) are used in the sensitivity analysis.

3.3.2 Definition of scenarios

Pareto fronts of (near) optimal sequence plans are developed for seven different scenarios (see Table 3). As pointed out by Mahmoud et al. (2009), the objective of scenario development is the identification of a small number of scenarios with plausible values of the uncertain variables that can potentially be significantly different in each scenario, resulting in alternative, though not equally likely, future states of the world. In the context of this case study, the purpose of the scenarios is to assess the impact of uncertainty on the ability of the optimal water supply augmentation sequences to satisfy the water supply security constraint (i.e. that supply is greater than or equal to demand), and the corresponding variation in objective function values. To this end, the different scenarios include combinations of the factors affecting water supply security (i.e. population growth and climate change impact) that result in the best possible future conditions with extremely low projected population growth and the least severe future climate change impact (Scenario 1) and the worst possible future conditions with extremely high projected population growth and severe climate change impact (Scenario 7). In this way, the solutions in the optimal portfolios of sequence plans obtained for the different scenarios will be able to meet the required water supply security constraint under a wide range of future conditions. It should be noted that a moderate discount rate is used for all scenarios, as the discount rate does not have a direct impact on future water supply security and hence the ability to meet the desired constraint under various plausible future conditions.

Table 3 Values of uncertain variables for the seven scenarios considered

Scenario	Population growth	Discount rate	Climate change impact
1	Extremely low	Moderate	Least severe
2	Very low	Moderate	Mild
3	Low	Moderate	Less severe
4	Moderate	Moderate	Moderate
5	High	Moderate	Severe
6	Very high	Moderate	Very severe
7	Extremely high	Moderate	Most severe

3.3.3 Development of Pareto fronts of diverse optimal sequences

The optimisation problem is formulated using nine decision variables, as summarised in Table 4. As the capacities of most of the water supply options are fixed (i.e. desalination, stormwater harvesting schemes), the decision variables correspond to the decision stage at which a particular option is implemented, ranging from 0 (the option is not implemented over the planning horizon) to 5 (the option is implemented at decision stage 5) (decision variables 1-4 and 6-9, Table 4). However, in addition to a decision variable for timing, rainwater tanks also have a decision variable corresponding to the capacity of the tanks (decision variable 5,Table 4), ranging from 1 to 10kL. It should be noted that the number of rainwater tanks implemented depends on the time of implementation, as the number of households changes over time.

As part of the optimisation process, populations of sequence plans are generated. These are then fed into the *WaterCress* simulation model in order to obtain estimates of supply, demand and operating costs and GHG emissions for the resulting water supply systems over the planning horizon. Next, the feasibility of the generated sequence plans is checked. This involves checking whether the simulated capacity of the selected system is greater than or equal to estimated demand at each decision stage and whether the generated combinations of options satisfy the feasibility criteria associated with the desalination plant (e.g. ensuring that the 50GL/year expansion occurs after the implementation of the original 50GL/year plant – see Section 3.2).

Table 4 Decision variables

Decision variable	Description	Lower limit	Upper limit
1	First 50GL desalination plant implementation stage	0	5
2	Second 50GL desalination plant implementation stage	0	5
3	50GL desalination plant expansion implementation stage	0	5
4	Household rainwater tank implementation stage	0	5
5	Household rainwater tank size (kL)	1	10
6	Brownhill & Keswick Creek stormwater harvesting scheme implementation stage	0	5
7	Sturt River stormwater harvesting scheme implementation stage	0	5
8	Field River stormwater harvesting scheme implementation stage	0	5
9	Pedler Creek stormwater harvesting scheme implementation stage	0	5

In order to develop the next generation of sequences, the Water System Multiobjective Genetic Algorithm (WSMGA) (Wu et al., 2010b) is used, which is based on the widely used multiobjective genetic algorithm NSGA-II (Deb et al., 2002). WSMGA uses the same operators as NSGA II, but is also able to cater to integer decision variables, which suits the formulation presented in Table 4. WSMGA has been used successfully in a number of multi-objective optimisation studies of water distributions systems considering cost and GHG emissions as objectives (Wu et al., 2010a; Wu et al., 2013; Wu et al., 2010b; Paton et al., 2014b).

3.4 Global Sensitivity Analysis

Sobol's method (Sobol, 1993) is used for the global sensitivity analysis, as it takes interactions between the uncertain variables into account, enables the direct contribution of each uncertain variable to be estimated via sensitivity indices and has been used successfully in a number of other environmental modelling applications (e.g. Kasprzyk et al., 2012, 2013; Nossent et al., 2011). Sobol's method is a variance-based method, in which the total variance of the model output, D(y), is decomposed into component variances from individual variables and their interactions

$$D(y) = \sum_{i} D_i + \sum_{i<j} D_{ij} + \sum_{i<j<k} D_{ijk} + D_{12\ldots m} \tag{1}$$

Where D_i = the variance due to the i^{th} variable x_i; D_{ij} = the variance from the interaction between x_i and x_j; D_{ijk}= the variance from the interaction between x_i, x_j, x_k; and m = the total number of variables (Sobol', 1993). Sobol's method is implemented using SimLab (Tarantola, 2005). In total, 192 samples are generated using Sobol's sampling method, resulting in 81 unique combinations of the uncertain variables. This is considered sufficient, as the size of the total search space is only 147 (i.e. 7x7x3).

The first order indices are used for assessing how the uncertain variables impact the output variables, as suggested by Saltelli et al. (2005) and Neumann (2012). The first order index is computed using

First-order index, $S_i = \frac{D_i}{D}$ (2)

where D_i= the variance due to the i^{th} uncertain variables ; D = the total variance of the model output.

In addition to the objectives (i.e. PV of cost and GHG emissions), reliability, which is a measure of how frequently supply capacity equals or exceeds demand, and vulnerability, which is a measure of demand shortfall, should demand exceed supply (Hashimoto et al., 1982), are used as performance measures. For ease of interpretation, vulnerability is expressed as the percentage shortfall of supply. Both reliability and vulnerability are calculated on an annual basis, as follows:

$$Reliability = \frac{T_s}{T} \tag{3}$$

where, T_s is the number of years that supply meets demand, and T is the length of the planning horizon (years).

$$Vulnerability = maximum \left(\frac{S_t}{A_t}\right) \tag{4}$$

where, S_t is the volume of annual supply shortfall for year t, and A_t is the total annual demand for year t.

In order to account for natural hydrologic variability, 20 replicates of 40 years of daily stochastic rainfall data are generated for each of the eight rainfall stations considered (see Figure 2) using the Stochastic Climate Library (SCL) (www.toolkit.net.au/scl). The SCL is used because it has the ability to generate rainfall at a number of temporal and spatial scales and has been applied successfully in a number of other studies (Srikanthan, 2005). A multi-site daily rainfall model is used for this case study because the available rainfall data are daily and because rainfall records are sourced from different stations. Further details of the generation of the stochastic rainfall time series are given in Paton et al. (2013) and Beh et al. (2014).

Climate variability is not taken into account for the monthly evaporation data due to limitations in SCL in relation to generating multi-site daily climate sequences and due to the fact that evaporation is less variable than rainfall. Consequently, as was done by Paton et al. (2013) for the same case study area, the historical evaporation data, adjusted for climate change impacts, are used.

The sensitivity analyses are repeated 20 times (i.e. the 20 sequences of 40 years of daily stochastic rainfall sequences are used as inputs to the simulation models of the various rainfall dependent sources in order to calculate total annual supply). Therefore, the results of the sensitivity analyses (i.e. variation in performance and sensitivity indices) are presented as averages over the sensitivity analyses with the 20 different stochastic rainfall series, as average values are common statistical metrics used for the direct comparison of model outputs (Bennett et al., 2013).

3.5 Selection of Optimal Sequence Plan

An informal process is used for selecting the optimal sequence plan, which includes consideration of:

- Trade-offs between the average values of the performance measures (i.e. PV of cost and GHG emissions, reliability and vulnerability) and their variation (including extreme values).
- The relative contribution of the uncertain variables (i.e. population, climate change, discount rate) to the variability in the performance measures and how easily they can be managed.
- The fact that the maximum vulnerability (i.e. supply shortfall) should be less than 27%, as this corresponds to the projected savings under Adelaide's highest level of temporary water restrictions i.e. level 5 restrictions (Chong et al., 2009). In other words, shortfalls greater than this will not be able to be avoided via temporary demand management measures that are within the control of the water authority.
- The degree of adaptability associated with different optimal sequences.

However, it should be noted that more formal approaches to multi-criteria decision-making could also be used (e.g. Hyde and Maier, 2006).

4 Results and Discussion

4.1 Determination of Portfolio of Diverse Optimal Sequences

The Pareto fronts of the optimal sequences for the seven plausible future scenarios considered are shown in Figure 4 and the selected portfolio of diverse optimal sequence plans is shown in Table 5. The optimal sequences considered as potential solutions (i.e. those included in Table 5) are selected because they include diversity in the actual solutions, as well as trade-offs between the objectives. A discussion of the differences between the solutions in Table 5 is given below.

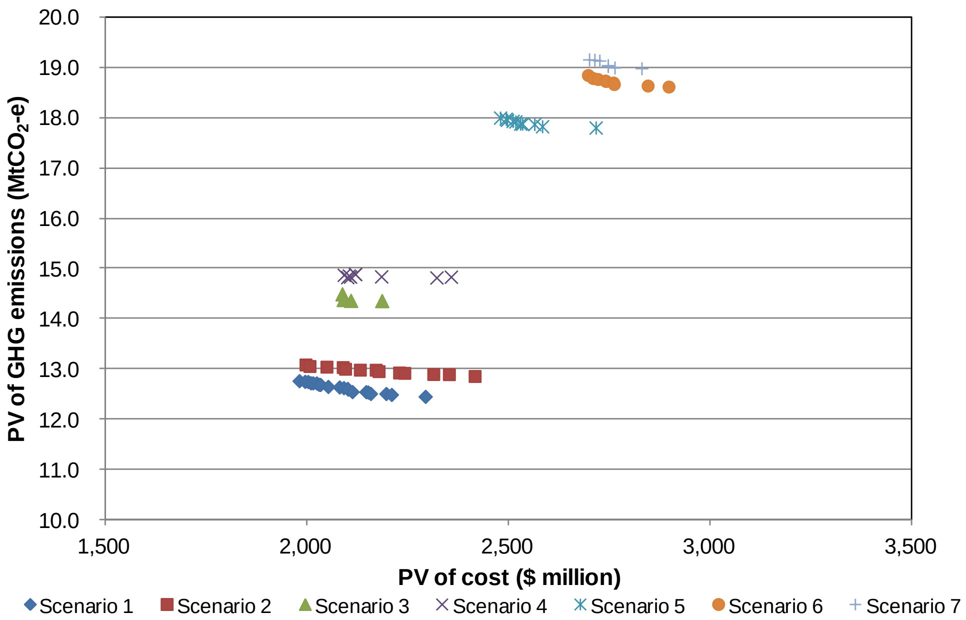

Figure 4 Tradeoff between PV of GHG emissions and PV of cost for the seven selected scenarios

Overall, it can be seen that the differences in objective function values between scenarios are significantly greater than those within scenarios. This is particularly the case for the GHG minimisation objective, where the range of PV of GHG emissions for a Pareto front developed for a particular scenario is relatively small compared with the jump in values of PV of GHG emissions between Pareto fronts. These jumps are caused by the discrete nature of the decision space and the inclusion of additional sources (e.g. the need to add the 50 GL desalination plant expansion in order to satisfy the water supply security constraint when moving from Scenario 2 to Scenario 3) or the inclusion of sources earlier on in the planning horizon (e.g. the need to add the 50 GL desalination plant expansion at decision stage 3, rather than decision stage 5, in order to satisfy the water supply security constraint when moving from Scenario 4 to Scenario 5).

It can also be seen that the objective function values for scenarios 1 and 2, 3 and 4 and 6 and 7 are quite close together, suggesting that the differences in conditions were insufficient to cause significant differences in optimal sequence plans. The PVs of costs range from ~$2.0 to ~$2.45 billion for the best case scenario to ~$2.7 to ~$2.9 billion for the worst case scenario. The PVs of GHG emissions range from ~$12.5 to ~$12.8 $MtCO_2$-e for the best case scenario to ~$19.0 to ~$19.15 $MtCO_2$-e for the worst case scenario.

As far as optimal supply augmentation is concerned, all optimal sequences include a 50GL desalination plant at stage 2. However, while all optimal sequences for scenarios 1 and 2 include the installation of 1kL rainwater tanks at 2050, this supply source is not featured in the optimal sequences for the other, more extreme scenarios, which include the addition of further desalinated supplies. Scenarios 3 and 4 include a 50GL desalination plant expansion at 2050, while this is moved forward to 2030 for scenarios 5 to 7 and an additional 50GL desalination plant is included in scenarios 6 and 7. All but one optimal sequence contain some stormwater harvesting, but the actual schemes and their timing vary considerably, primarily accounting for the trade-offs between PVs of cost and GHG emissions, as discussed below.

Table 5 Details of selected portfolio of diverse optimal sequence plans

Sequence plan	Decision stage at which to implement water supply options (1 = 2010, 2 = 2020, ... etc)									Present value of cost ($ million)	Present value of GHG emissions ($MtCO_2$-e)
	50GL desalination plant	50GL desalination plant	50GL desalination plant expansion	Household rainwater tank	Rainwater tank capacity (kL)	Brownhill and Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme		
Scenario 1											
1	2	0	0	5	1	0	0	0	0	1,979.60	12.77
2	2	0	0	5	1	0	4	0	0	2,022.41	12.72
3	2	0	0	5	1	1	0	0	5	2,089.76	12.63
4	2	0	0	5	1	2	4	0	2	2,145.18	12.55
5	2	0	0	5	1	0	2	0	1	2,292.52	12.45
Scenario 2											
6	2	0	0	5	1	0	0	5	0	1,995.51	13.09
7	2	0	0	5	1	0	4	0	3	2,087.83	13.04
8	2	0	0	5	1	0	3	0	2	2,169.69	12.98
9	2	0	0	5	1	1	0	0	1	2,240.68	12.92
10	2	0	0	5	1	0	1	0	1	2,415.15	12.86
Scenario 3											
11	2	0	5	0	0	3	0	4	0	2,086.17	14.49
12	2	0	5	0	0	1	5	0	5	2,184.68	14.36
Scenario 4											
13	2	0	5	0	0	3	0	5	0	2,090.52	14.87
14	2	0	5	0	0	3	0	5	5	2,102.94	14.86
15	2	0	5	0	0	3	0	5	4	2,118.31	14.89
16	2	0	5	0	0	1	5	0	0	2,183.29	14.84
17	2	0	5	0	0	1	4	0	1	2,356.28	14.84
Scenario 5											
18	2	0	3	0	0	5	0	0	5	2,478.53	18.00
19	2	0	3	0	0	0	5	0	5	2,495.50	17.96
20	2	0	3	0	0	3	0	0	3	2,528.27	17.88
21	2	0	3	0	0	3	4	0	3	2,563.33	17.87
22	2	0	3	0	0	0	3	0	1	2,715.63	17.80
Scenario 6											
23	2	5	3	0	0	2	0	0	0	2,696.28	18.85
24	2	5	3	0	0	2	0	0	4	2,720.46	18.77
25	2	5	3	0	0	2	0	0	3	2,740.48	18.73
26	2	5	3	0	0	0	5	0	2	2,760.80	18.67
27	2	5	3	0	0	0	3	0	1	2,896.41	18.62
Scenario 7											
28	2	5	3	0	0	2	0	0	5	2,712.53	19.15
29	2	5	3	0	0	5	0	0	2	2,745.67	19.05
30	2	5	3	0	0	0	5	0	1	2,829.28	18.99

In relation to the trade-offs between the two objectives, it can be seen from Table 5 that the use of stormwater harvesting is more attractive from a GHG emission perspective than from a cost-perspective, as evidenced by the fact that the stormwater harvesting schemes are generally implemented earlier in the planning horizon when optimising for GHG emissions than when optimising for cost. For example, some of the stormwater schemes are implemented at the first decision stage although the existing water supply sources are sufficient to meet demand. This is because the GHG emissions per unit volume from the stormwater sources are lower than supply from the River Murray due to the need to pump River Murray water to the Onkaparinga River via the Murray-Onkaparinga pipeline and then to transfer it to other storage reservoirs (see Figure 2). Consequently, even though there is sufficient supply to meet demand during the early stages of the planning horizon from existing and already selected sources, there is some benefit in terms of GHG emission reduction in implementing stormwater harvesting schemes and replacing some of the non-potable supply from the River Murray with that obtained from the stormwater harvesting schemes. In contrast, for sequence plans with lower PV of cost, stormwater harvesting schemes are implemented later in the planning horizon because the supply from the existing sources, such as Happy Valley reservoir, Myponga reservoir and the River Murray, and the 50GL desalination plant (implemented at the second stage), offer lower unit operating costs (Table 1).

4.2 Global Sensitivity Analysis

4.2.1 Sensitivity of performance of optimal sequence plans to uncertain variables

The box-and-whiskers plots in Figure 5 show the variation of the average values (over the 20 stochastic rainfall sequences) of the PV of cost, the PV of GHG emissions and system reliability and vulnerability over the combinations of uncertain variables considered as part of the sensitivity analysis for the 30 selected sequences. As can be seen, there is a slight increase in the variation in the PVs of cost and GHG emissions for solutions with higher average values, suggesting reduced robustness. However, these solutions are significantly more robust (less variable) with respect to reliability and especially vulnerability. This is because solutions with higher average PVs of cost and GHG emissions are optimal for more extreme scenarios and are therefore able to meet the required demand under a wider range of plausible future conditions. Consequently, the most significant trade-offs exist between increased PVs of cost and GHG emissions (both in terms of average values and variation) and water supply security, as measured by the average values of and variation in reliability and vulnerability. Specifically, there is a noticeably increase in reliability and a significant reduction in vulnerability (average and variability) from solution 18 onward, which is due to the earlier sequencing of the 50 GL desalination plant expansion. However, the vulnerability (average and variability) of sequence 17 is also noticeably lower than that of sequences 1 to 16, which is due to the implementation of a number of stormwater schemes earlier in the planning horizon in order to reduce the PV of GHG emissions.

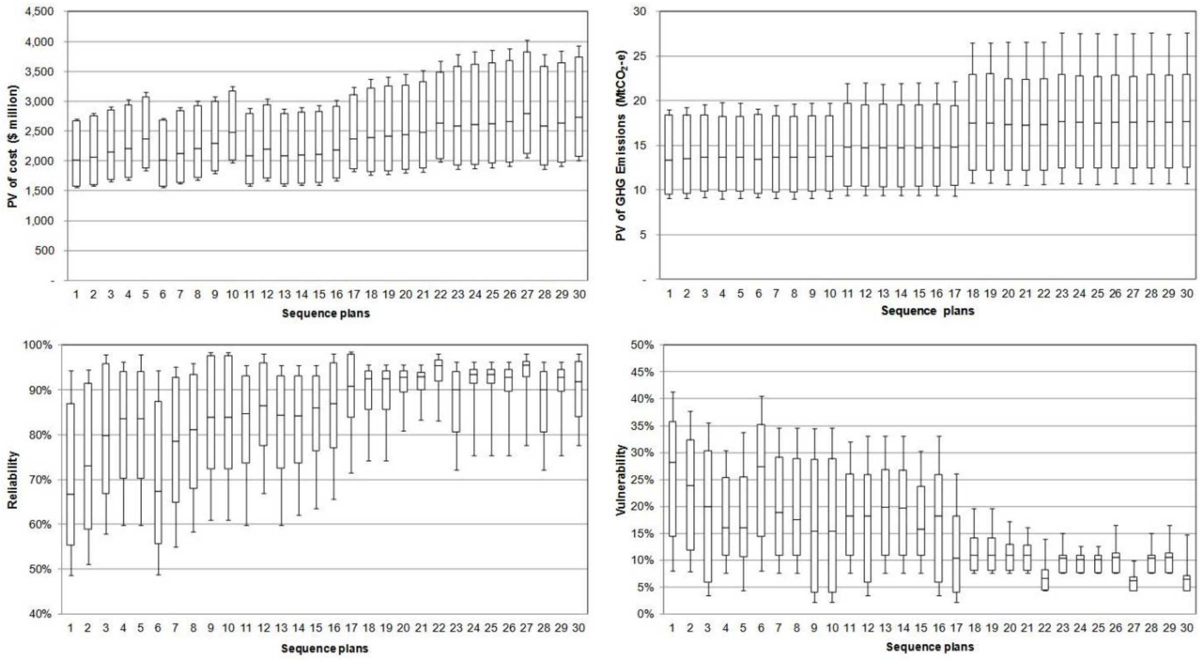

Figure 5 Variation in average performance values (over the 20 stochastic rainfall sequences) of the selected optimal sequence plans over the combinations of uncertain conditions considered as part of the sensitivity analysis. It should be noted that vulnerability is not zero for optimal sequences developed for the most extreme scenario due to effects of climate variability.

4.2.2 Relative influence of uncertain variables on performance of optimal sequence plans

The plots of the ranges of the Sobol sensitivity indices for the selected optimal sequences (Table 5) are given Figure 6. As can be seen, the PVs of cost and GHG emissions are primarily affected by changes in discount rate, with a small impact due to changes in population growth and climate change. This is not surprising, as discount rates have a direct impact on the PVs of cost and GHG emissions. However, capital costs are fixed for a particular plan over the combinations of uncertain conditions considered as part of the sensitivity analysis. Consequently, the only changes in the PVs of costs and GHG emissions due to changes in population growth and climate change are because of changes in operational costs. However, changes in operational costs are constrained by the capacity of the various water supply sources. If demand equals the maximum capacity of a selected system, then changes in population growth or climate will not have any impact on the PVs of cost and GHG emissions, as operational costs and GHG emissions are already at their maximum, whereas system reliability will be reduced and system vulnerability will be increased. In cases where there is a slight excess capacity in the system, there is some scope to increase system yield, thereby increasing operational costs and GHG emissions. This capacity is greater for systems with higher-cost optimal sequences, as discussed earlier, resulting in a slight variation in the sensitivity indices over the selected sequence plans.

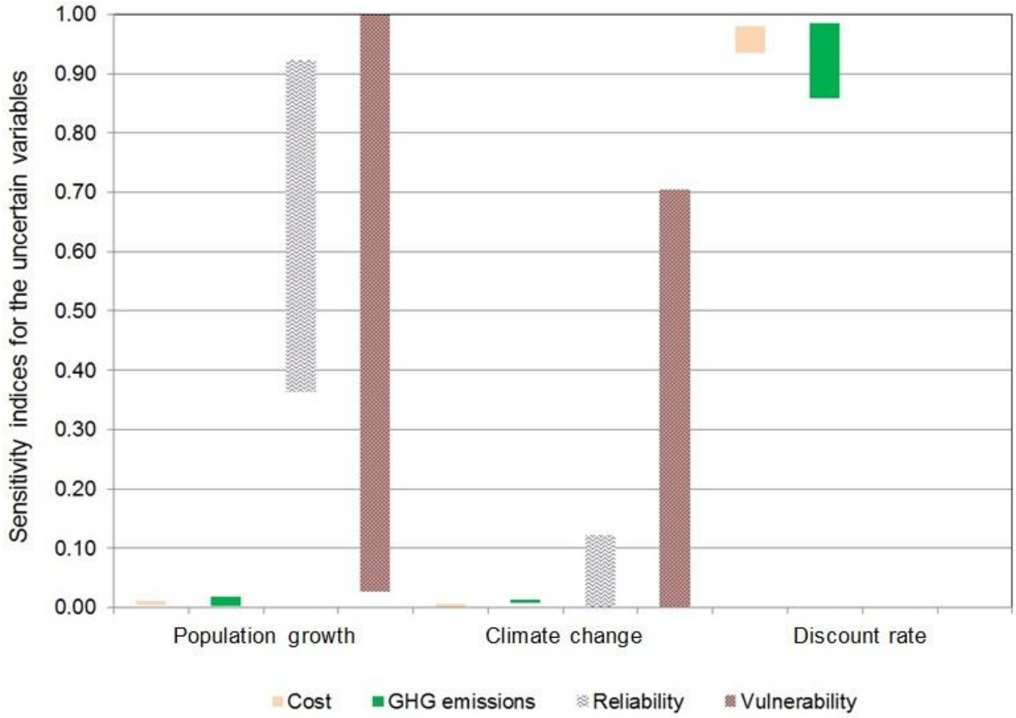

Figure 6 Ranges of Sobol's first order sensitivity indices for cost, GHG emissions, reliability and vulnerability over the combinations of uncertain conditions for the selected optimal sequence plans

In contrast to the PVs of cost and GHG emissions, reliability and vulnerability are sensitive to changes in population growth and climate change, but not discount rate (Figure 6). This is as expected, as reliability and vulnerability are a function of supply and demand, which are not affected by discount rate, but rather the size of the population (i.e. demand) and climate (i.e. rainfall and evaporation). However, there is a large variation in the sensitivity indices for the different optimal sequences. This is primarily a function of supply availability from the stormwater harvesting schemes, given that the timing of the implementation of the 50GL desalination plant and its expansion are common to most optimal sequences and that many of the major supply sources, including the River Murray, which is subject to a licensing agreement (see Beh et al., 2014), and the desalination plant, are climate independent for the purposes of this study. Consequently, changes in climate only have a significant impact on supply availability from the reservoirs, the stormwater harvesting schemes and the rainwater tanks.

4.3 Selection of Optimal Sequence Plan

A major consideration in the selection of the optimal sequence plan is the fact that maximum vulnerability should not exceed 27%, as this is the largest shortfall that can be managed through the most severe temporary water restrictions, as discussed in Section 3.5. Consequently, sequence plans 1 to 16 are excluded from further consideration, as their maximum vulnerabilities exceed 27% and could therefore result in actual water shortages. It should be noted that although population growth is beyond the control of the water authority, it is a surrogate for demand and the fact that vulnerability is sensitive to population (Figure 6) suggests that demand management would be effective in managing demand shortfalls.

Of the optimal sequences for which maximum vulnerability is less than 27% (i.e. 17 to 30), the major trade-offs occur between sequence 17 and the remaining sequences. Sequence 17 just satisfies the maximum vulnerability criterion with a maximum vulnerability of 24% and has slightly lower reliability than the other sequences, but the PVs of cost and GHG emissions are considerably lower. This is because in sequence 17, the 50GL desalination plant expansion does not occur until 2050, whereas it occurs at 2030 in sequences 18 to 30.

Given that the maximum shortfall can be managed via demand restrictions for sequence 17 and that its PVs of cost and GHG emissions are significantly lower than for sequences 18 to 30, it is suggested that this sequence should be selected for implementation. In making this decision, it should be noted that the maximum shortfall is much less than 24% under the majority of plausible future conditions, as indicated by the variation in the box-and-whiskers plot for sequence 17 in Figure 5, indicating that level 5 restrictions would only be required under a few extreme cases. In addition, sequence 17 has greater adaptability than sequences 18 to 30. As the desalination plants represent the largest capital investment (in terms of cost and GHG emissions) and all optimal sequences include a 50GL desalination plant at decision 2020, it is desirable to delay the 50GL expansion of the desalination plant as much as possible in order to be able to respond to actual conditions as time progresses, while ensuring adequate water supply security. Consequently, sequence 17 is preferred, as it does not require the 50GL desalination plant expansion until 2050, compared with 2030 for sequences 18 to 30. For example, if the desalination plant expansion was built in 2030 and subsequent population growth and/or climate change impacts were favourable, there would be a large amount of excess water supply capacity for sequences 18 to 30, with associated unnecessary capital costs and GHG emissions. In contrast, this would not be the case for sequence 17, as there would be greater capacity to respond to actual conditions.

5 Summary and Conclusions

In this paper, a scenario driven approach to the optimal sequencing of environmental and water resources activities under deep uncertainty is introduced. As part of the approach, a diverse portfolio of optimal sequence plans is generated by obtaining optimal sequences under a range of plausible future scenarios and selecting optimal sequences that are diverse in terms of solutions and trade-offs between objectives. Next, global sensitivity analysis is performed on the selected sequences to assess the variation (robustness) of system performance under a wide range of plausible future conditions and to determine the relative contribution of the uncertain variables to the variation in system performance. The above steps identify a small subset of sequence plans that provide the optimal trade-offs between objectives for a range of future scenarios, as well as information on the robustness of these solutions, from which decision-makers can select their preferred solution using formal or informal multi-criteria decision-analysis methods.

For illustration purposes, the above approach is applied to the urban water supply augmentation sequencing for a case study based on the southern Adelaide water supply system in 2010 that has been studied previously in a deterministic setting (Beh at al., 2014). The augmentation options considered include various desalination, rainwater and stormwater harvesting alternatives. The planning horizon considered is 40 years, with a staging interval of 10 years, resulting in 5 decision stages. The objectives considered include cost and GHG emissions and optimal augmentation sequences are developed for seven scenarios consisting of different future population, climate change and discount rate values. From the Pareto fronts obtained for these scenarios, 30 sequences are selected to form the portfolio of diverse solutions.

Sobol' is used as the global sensitivity analysis method and reliability and vulnerability are used as performance measures in addition to the objectives. Based on the results of the sensitivity analysis, and consideration of other relevant criteria, such as adaptability and the ability to meet demand shortfalls with the aid of temporary water restrictions, an optimal sequence is selected that provides a good compromise between average and extreme values of the performance measures, as well as the ability to adapt to actual future conditions. The selected optimal sequence plan includes implementation of the Pedler and Brownhill & Keswick Creek stormwater harvesting schemes in 2010, the construction of a 50GL desalination plant in 2020, the implementation of the Sturt River stormwater harvesting scheme in 2040 and a 50GL expansion of the desalination plant in 2050.

As part of the case study, informal approaches are used for the identification of appropriate scenarios and the selection of the final optimal sequence. However, the development of more formal approaches for achieving this, such as scenario discovery (e.g. Kasprzyk et al., 2013; Lempert and Groves, 2010) and multi-criteria decision analysis (Hyde and Maier, 2006; Korteling et al., 2013), could be investigated in future research, especially for more complex problems. In addition, even though adaptability is considered post-optimisation, it is not included as part of the formal optimal sequencing process in this study. This should be undertaken in future research. In addition, there is also scope to consider how the formulation of the optimisation problem might change over time (Maier et al., 2014; Piscopo et al., 2015). Finally, as part of the proposed approach, robustness is not considered explicitly as an objective during the optimisation process and future research could focus on the development of approaches that are sufficiently computationally efficient to enable robustness measures to be considered as objectives in the optimisation process (Maier et al., 2014).

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