Optimal Sequencing of Water Supply Options Incorporating Sustainability and Uncertainty

by

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Contents

Abstract

Sequencing of water supply projects involves choosing the options to implement at specific stages over a planning horizon. In the past, the sequencing of water supply projects was relatively straightforward and generally focused on traditional water supply sources (e.g. reservoirs and groundwater sources) and only considered the criteria of water supply security and cost. In recent years, the reliability of traditional water supply sources has been compromised as a result of increasing demand and the impact of climatic factors. This has placed further strain on water supplies and necessitated the use of a longer planning horizon and more criteria for assessment. Furthermore, with the increase in urbanisation and diminishing natural water sources, there is an increase in the need to consider recycled water and desalination as additional or alternative water supply options. Extended planning horizons result in increased uncertainties associated with the future, which requires the development of robust and adaptive solutions to best cope with a variety of potential future conditions. However, there has been little work that has utilised alternative water supply sources in the process of sequencing while incorporating multiple sustainability objectives and uncertainties.

This thesis presents different sequencing approaches that are based on multi-objective optimisation, so that a number of competing objectives (e.g. cost, greenhouse gas emissions) can be taken into account. Furthermore, the optimal mix of water supply options, and when they should be implemented, can be identified from among a large number of alternatives (e.g. rainwater tanks, stormwater harvesting schemes, desalination etc.). In addition, some of the proposed optimisation approaches take the sensitivity, robustness and adaptation of solutions into account, so that the selected water supply options will be as insensitive and flexible to future changes (e.g. climate change, new technologies) as possible. The proposed sequencing approaches are applied to a case study based on the southern Adelaide water supply system in South Australia to demonstrate its utility.

This thesis is structured as a series of three publications. Two approximate optimal sequencing approaches that are able to account for alternative sources of water and multiple sustainability objectives are introduced in the first publication. These approaches are developed to assess the impact of different objective function weightings and sequencing approaches on the optimal sequences of alternative water supply sources for the case study under a range of demand and discount rate scenarios. They are also used to assess the impact of different objective function weightings on objective function values for the case study.

The second publication includes an improved sequencing approach, which utilises a multi-objective evolutionary algorithm, coupled with a water supply system simulation model, to identify the sequences

of alternative water supply sources that represent the optimal trade-offs between the selected objectives for various possible future conditions Subsequently, the impacts of uncertain values of input variables (e.g. population, per capita demand, climate change) on the objectives and water supply security of the system are evaluated using global sensitivity analysis. This provides information on the expected variation in objective function values and water supply security under uncertain future conditions, as well as the sensitivity of these values to the selected uncertain conditions, enabling the most appropriate optimal sequence plan to be selected.

In the third publication, this sequencing approach is further extended to a more enhanced framework which promotes robustness and adaptation. This approach requires continual reassessment and updating of the sequence plans at fixed time intervals in order to identify and reduce the risk of failure.

Statement of Originality

I certify that this work contains no material which has been accepted for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. In addition, I certify that no part of this work will, in the future, be used in a submission for any other degree or diploma in any university or other tertiary institution without the prior approval of the University of Adelaide and where applicable, any partner institution responsible for the joint-award of this degree.

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I would like to thank The Goyder Institute for Water Research in supporting this research study. In addition, would like to acknowledge David Cresswell, who developed the *WaterCress* simulation model, for his technical assistance. Furthermore, I am very grateful to Wenyan Wu, for the opportunity to work with the WSMGA source code, for her helpful assistance with running the program. I also like to thank Stephen Carr for his kind assistance in providing extra machines for running the models.

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I would like to thank my parents and my sister Phoebe for their reliance and understanding over the years. I would also like to thank my husband, Jian Lim; I would not have come this far without his unwavering support on this journey.

Lastly, I dedicate this thesis to my beloved late grandfather, B.G. Beh.

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Chapter 1

1 Introduction

Sequencing of water supply sources involves choosing the options to implement and their timing over a defined planning horizon. This allows water supply sources to be introduced when they are needed, and reduces redundancy and therefore costs associated with the system. The optimal sequencing of urban water supply sources has long been used to identify water supply projects that maintain water supply security, but has traditionally focused on the reservoir expansion problem and economic objectives (Becker and Yeh, 1974, Butcher et al., 1969, Morin and Esogbue, 1971, Connarty and Dandy, 1996). However, as a result of increased climate variability and change, increased water demand due to population and urban growth and increased efforts to adopt sustainable water management practices, the complexity of this optimal sequencing task has increased significantly, as illustrated in Figure 1.1.

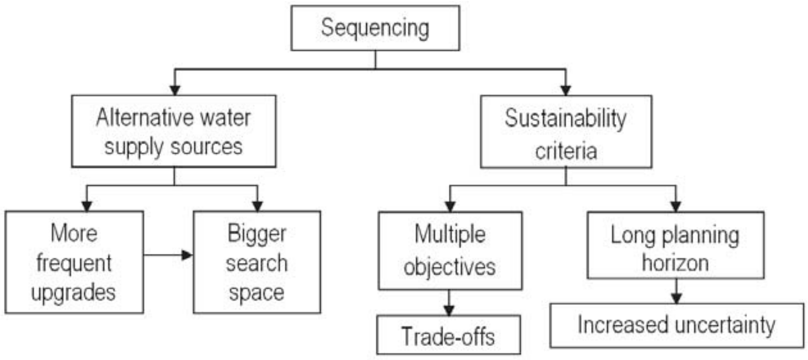

Figure 1.1 Criteria involved in the sequencing of sustainable water supply sources

Firstly, in order to respond to increased demand, there has been a significant increase in the use of alternative, non traditional sources of water, such as desalination, stormwater re-use and rainwater tanks in order to increase water supply security in times of drought and in response to potential climate change impacts (Kang and Lansey, 2012, Coombes and Lucas, 2006). This has resulted in a significant increase in the number of alternative water sources that need to be included in the sequencing process and increased the frequency with which water supply systems are upgraded, as many of the alternative sources of water have small capacities. This makes it difficult to ascertain which combination of sources is best and when certain sources should be developed and brought online, as the number of potential solutions is significantly greater than had been considered for conventional systems.

Secondly, the adoption of sustainability principles also increases the complexity of the sequencing problem due to the need to consider a variety of alternative objectives, such as environmental, social and technical objectives, in addition to the traditional focus on economic objectives (Hellstrom et al., 2000) (Figure 1.1). As a result, there is no longer a single optimal solution, as many of these objectives are in competition with each other. This leads to the need to identify solutions that represent the optimal trade-offs between these objectives.

Thirdly, the adoption of sustainability principles requires consideration of extended time frames, such as 50 to 100 years in the planning of water resources projects (Mitchell et al., 2007) (Figure 1.1). This further complicates the sequencing task, as conditions, such as population, climate and technology are likely to change substantially over extended timeframes (Tanaka et al., 2006), making it more difficult to assess the relative merits of optimal sequencing plans (Beh et al., 2011). While significant progress has been made in the development of techniques for quantifying the uncertainty associated with future demand and hydrological forecasts (Zhang et al., 2013, Kuczera and Mroczkowski, 1998, Mantovan and Todini, 2006, Ajami et al., 2007, Chung et al., 2009), the uncertainty associated with other factors affecting the sequencing or urban water supply sources, such as discount rates and climate change, are more difficult to assess.

Previous studies on the sequencing of water supply projects have generally been applied to traditional water supply sources, for instance, the expansion of multiple reservoirs (Braga et al., 1985, Dandy and Connarty, 1994) and groundwater supplies (Chang et al., 2009), without consideration of alternative sources of water. Furthermore, economic costs were the sole criterion for determining the best sequence of water supply options. For example, Mulvihill and Dracup (1974) determined the optimal blending of several water sources, and the sizing and timing of their expansion by minimising the sum of the capital, operational and maintenance costs of a system. Later, Rubinstein and Ortolano (1984) and Martin (1987) determined the optimal sequence by minimising the total construction costs required to establish a system that could cope with emergencies that threatened the supply of water. However, there has been a lack of consideration of other objectives.

Existing optimal sequencing approaches for water supply sources are generally deterministic, in the sense that they require assumptions to be made about future conditions, such as population growth, per capita demand and hydrological inputs. While this results in optimal sequence plans if the assumed future values are correct, it has been widely acknowledged that this is unlikely to be the case (e.g. (Dessai et al., 2013, Gober, 2013). Consequently, there is a need to consider various sources of uncertainty in the optimal sequencing of water supply sources.

Although there are a variety of methods developed to deal with uncertainty for the determination of robust portfolios of future water supply and demand management options (e.g. Kasprzyk et al., 2013b, Kasprzyk et al., 2012, Kasprzyk et al., 2009, Matrosov et al., 2013a, Matrosov et al., 2013b, Korteling et al., 2013), they have generally not been extended to consider the sequencing or scheduling of water supply sources, except for a number of exceptions (Ray et al., 2012; Kang and Lansey, 2014).

Robustness is generally understood as the ability to withstand external shocks or to be stable under a range of uncertainties (Bankes, 2010). However, when the sequencing of water supply sources is considered, adaptation (i.e. changing the solutions to be implemented at each decision point in response to changes in the assumptions) can be considered as a way of dealing with uncertainty in addition to robustness (i.e. selecting solutions that are insensitive to changes in future conditions). This has been demonstrated in the areas of water distribution system design (Basupi and Kapelan, 2013) and flood management (Woodward et al., 2014). Only Lempert and Groves (2010) considered both robustness and adaptation in the context of the sequencing of water supply sources, although they did not utilise a formal optimisation approach.

1.1 Research Objectives

This research aims to enhance the traditional sequencing approach by incorporating multiple sustainability criteria (i.e. economic, environmental and robustness), alternative water supply sources (i.e. reservoirs, desalination plant and stormwater) and different sources of uncertainty (i.e. population growth, per capita demand, climate change, climate variability, etc.). The specific research objectives are given below.

Objective 1: Development of innovative approaches to the optimal sequencing of urban water supply options that cater for multiple objectives and alternative sources of water.

Objective 2: Development of innovative approaches to the optimal sequencing of urban water supply options that enable optimal sequence plans to be identified under deep uncertainty by:

> **Objective 2.1**: Using a static approach based on global sensitivity analysis.
>
> **Objective 2.2**: Using an adaptive approach based on flexibility and robustness.

Objective 3: To demonstrate and test the utility of the different approaches on a case study based on the expansion of the southern Adelaide water supply system

1.2 Thesis Overview

This thesis is organised into five chapters. The main body of this thesis consists of **Chapters 2** to **4**, which correspond to three journal papers (Beh et al., 2014, Beh et al., 2015a, Beh et al., 2015b).

In **Chapter 2**, two approximate optimal sequencing approaches, the “Build–up” (BU) and “Build to target” (BTT) methods, are developed to identify optimal sequence plans that include alternative urban water supply sources and multiple objectives (Objective 1) under a range of demand and discount rate scenarios, where the impact of different objective function weightings and sequencing approaches on: (i) the optimal sequences of alternative water supply sources, and (ii) the objective function values are assessed. The utility of the proposed approach is demonstrated on the case study of southern Adelaide water supply system (Objective 3). The results obtained show that the BU method generally results in less favourable objective function values, but is more flexible and responsive to future changes compared with the BTT method.

In Chapter 3, a multi-objective approach to the optimal sequencing of environmental and water resources activities under deep uncertainty is developed (Objectives 1 and 2.1). The approach consists of three main steps, including (i) the determination 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/ schedule to be implemented. The proposed approach is applied to the case study of southern Adelaide water supply system (Objective 3). Based on the results obtained, the proposed sequencing approach provides sequences with good compromise between average and extreme values of the performance measures, as well as the ability to adapt to actual future conditions.

In Chapter 4, the work in **Chapter 3** is further extended to incorporate robustness and adaptation (Objectives 1 and 2.2) when identifying the sequences of alternative water supply sources that cater for multiple objectives under deep uncertainty. The proposed robust, adaptive, multi-objective optimal sequencing approach consists of three steps, including (i) identification of a diverse portfolio of optimal water supply augmentation sequence plans over the entire planning period with the aid of scenario-based multi-objective optimisation, (ii) assessment of the performance of the portfolio of optimal sequence plans in terms of robustness and flexibility over the current staging interval and variation of the optimisation objectives over the entire planning period and (iii) selection of the water supply option(s) to be implemented at the current decision stage based on the trade-offs between the performance criteria in (ii). The above steps are repeated at subsequent decision stages (e.g. if the staging interval is 10-years, this process will be repeated every 10 years). The enhanced approach is also applied to the same case study in order to demonstrate its utility (Objective 3). The results indicate that the approach is successful in adapting to changing conditions, while optimising longer-term objectives and satisfying water supply security constraints along the planning horizon, in highly uncertain planning environments.

The linking of each of the papers to the objectives is depicted in Table 1.1. Although the manuscripts have been reformatted in accordance with University guidelines, and sections renumbered for inclusion within this thesis, the material within this paper is otherwise presented herein as published. Copy of the publication "as published" are provided in Appendix.

Conclusions of the research within this thesis are provided in **Chapter 5**, which summarises: 1) the research contributions, 2) limitations and 3) future directions for further research.

Table 1.1 Linkage of research objectives and publications

		Paper 1	Paper 2	Paper 3
1.	To develop innovative approaches to the optimal sequencing of urban water supply options that cater for multiple objectives and alternative sources of water.	X	X	X
2.	To develop innovative approaches to the optimal sequencing of urban water supply options that enable the optimal sequence plan to be identified under deep uncertainty by:			
	2.1 Using a static approach based on global sensitivity analysis.		X	
	2.2 Using an adaptive approach based on flexibility and robustness.			X
3.	To demonstrate and test the utility of the different approaches on a case study based on the expansion of the southern Adelaide water supply system.	X	X	X

Chapter 2

2 Optimal sequencing of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives – Paper 1

Statement of Authorship

Title of Paper	Optimal sequencing of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives
Publication Status	◉ Published ○ Accepted for Publication ○ Submitted for Publication ○ Publication Style
Publication Details	Beh, E.H.Y., Dandy, G.C., Maier, H.R., Paton, F.L., 2014. Optimal sequencing of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives. Environmental Modelling & Software 53 137-153.

Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

Name of Principal Author (Candidate)	Eva Beh
Contribution to the Paper	Conceptualisation and development of approach, modelling, analysis of results, preparation of manuscript.
Signature	Date 1/4/2015

Name of Co-Author	Graeme Dandy
Contribution to the Paper	Research supervision and review of manuscript.
Signature	Date 1/4/2015

Name of Co-Author	Holger Maier
Contribution to the Paper	Research supervision and review of manuscript.
Signature	Date 01/04/15

Name of Co-Author	Fiona Paton
Contribution to the Paper	Calibration of the climate date for the case study and review of manuscript.
Signature	Date 1/4/15

Abstract

In recent years, the sequencing of water supply projects has become increasingly complex, as a result of the need to consider alternative water sources and additional objectives. In order to address this problem, two sequencing approaches are presented in this paper to assist in identifying the optimal sequence of water supply projects. The methods are applied to a case study based on the southern Adelaide water supply system, South Australia, over a 40-year planning horizon. Desalination plants, rainwater and stormwater sources are considered in addition to existing surface water sources. The objectives used include the present value of cost and greenhouse gas (GHG) emissions and optimal sequences are obtained for a range of demand and discount rate scenarios. The results demonstrate that there are noticeable tradeoffs between costs and GHG emissions when favouring different objectives, but that the impacts of uncertain demands and discount rates are potentially more significant.

2.1 Introduction

Sequencing has long been used to identify water supply projects that maintain water supply security and minimise water supply costs (Butcher et al., 1969). For example, Morin et al. (1971) determined the optimum sequence for the implementation of potential water supply projects to meet scheduled demand with minimum present value of cost and UK Water Industry Research (2002) presented an approach to the minimum-cost sequencing of surface and groundwater supply projects. Techniques for sequencing have generally been applied to traditional water supply sources, for instance, the expansion of multiple reservoirs (Dandy and Connarty, 1994, Braga et al., 1985, Becker and Yeh, 1974) and groundwater supply (Chang et al., 2009). However, in recent years, confidence in such traditional water supply sources, such as reservoirs and groundwater supplies, has waned as a result of increasing demand and reduced reliability of supply due to climate factors (Chartres and Williams, 2006).

In response, there has been a significant increase in the use of alternative sources of water, such as desalination, reclaimed wastewater and harvested stormwater and rainwater, in an attempt to improve water supply security in times of drought and in response to potential climate change impacts (Coombes and Lucas, 2006). These alternative sources have been found to be efficient in terms of the augmentation of water supply systems and in easing pressure on traditional water resources (Eroksuz and Rahman, 2010, Voivontas et al., 2003, Zhang et al., 2013).

However, such non-traditional sources have not been considered as part of sequencing studies to date. Consequently, there is a need to develop a sequencing approach that includes non-traditional sources. This is particularly the case as their consideration increases the complexity of the sequencing problem because of the larger number of potential water supply options. Furthermore, sequencing must accommodate the smaller capacities of localized sources of water, such as rainwater, stormwater and greywater, and may therefore have to be conducted more frequently.

In previous sequencing studies, economic cost was used as the primary criterion for determining the best sequence of water supply options. For example, Mulvihill and Dracup (1974) determined the optimal blending of several water sources, and the sizing and timing of their expansion by minimising the capital, operational and maintenance costs of the system. Later, Rubinstein and Ortolano (1984) and Martin (1987) determined the optimal sequence by minimising the total construction costs required to establish a system that could cope with emergencies in the supply of water. However, in the last two decades, the need to develop sustainable water supply systems has become increasingly important (Gleick, 1998), requiring the consideration of multiple objectives, including not just economic, but also environmental, social, technical and temporal criteria (Hellstrom et al., 2000).

In order to address the shortcomings of existing sequencing approaches discussed above, the objectives of this paper are (i) to present two sequencing approaches that are able to account for alternative sources of water, shorter staging intervals and multiple objectives, (ii) to demonstrate the utility of the approaches by applying them to the case study based on the southern portion of the water supply system for Adelaide, South Australia (SA), (iii) to assess the impact of different objective function weightings and sequencing approaches on the optimal sequences of alternative water supply sources for the case study under a range of demand and discount rate scenarios; and (iv) to assess the impact of different objective function weightings and sequencing approaches on objective function values for the case study.

The remainder of this paper is organized to firstly discuss the two proposed sequencing approaches that consider multiple objectives and alternative, non-traditional sources of water (Section 2.2). The case study, and the application of the proposed approaches to the case study, are described in Sections 2.3 and 2.4; and the results obtained are presented and discussed in Section 2.5. Conclusions and recommendations are offered in Section 2.6.

2.2 Proposed Sequencing Approaches

The sequencing approaches introduced in this paper involve subdividing the planning horizon T (e.g., 50 years) into a finite number of staging intervals t (e.g., five years) resulting in a number of decision stages P_y =1, 2, 3, ..., r (e.g. if T = 50 years and t = 5 years, r =50/5=10, resulting in 10 decision stages, each with a duration of 5 years) (Figure 2.1). For each stage, different potential water supply options S_x (x=1, 2, 3, ..., q)

are considered, such as reservoirs, stormwater reuse and desalination, along with a set of finite integer capacities C_x, ranging from zero to a maximum value, as illustrated in Figure 2.1.

It should be noted that for each decision stage, water supply Q_x, taken from each water supply option, should not exceed the selected capacity C_x. Furthermore, the total water supply must satisfy the projected demand at each decision stage, which acts as a constraint on the sequencing problem (Figure 2.1).

The purpose of the sequencing process is to select the combination of sources and capacities at the beginning of each staging interval (i.e., at each decision point) so as to optimise one or more objectives O_s (s=1, 2, 3, ..., p), such as cost, energy usage and reliability, while satisfying the constraints identified (Figure 2.1).

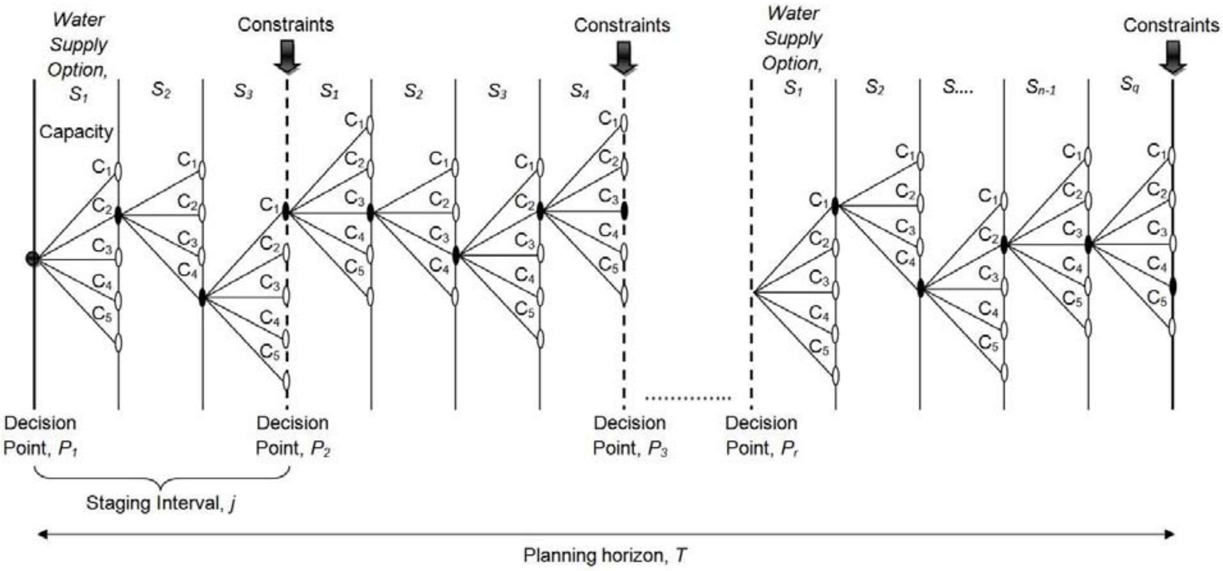

Figure 2.1 Proposed problem representation

In order to implement either of the proposed sequencing approaches, three major steps need to be taken. The first step is *problem formulation*, which includes selecting appropriate objectives to be maximised or minimised, setting the planning horizon and interval between review periods, defining the demand constraints over the planning horizon, and choosing potential water sources and capacities. The next step involves the *calculation of the yields for each potential water supply option*. The third step is the *sequencing process*, during which the best combination of sources to meet the demand is selected. Each of these steps is described in detail in the subsequent sections.

2.2.1 Problem Formulation

In the problem formulation stage, the objectives, planning horizon, demand and possible water supply options need to be selected, as shown in Figure 2.2.

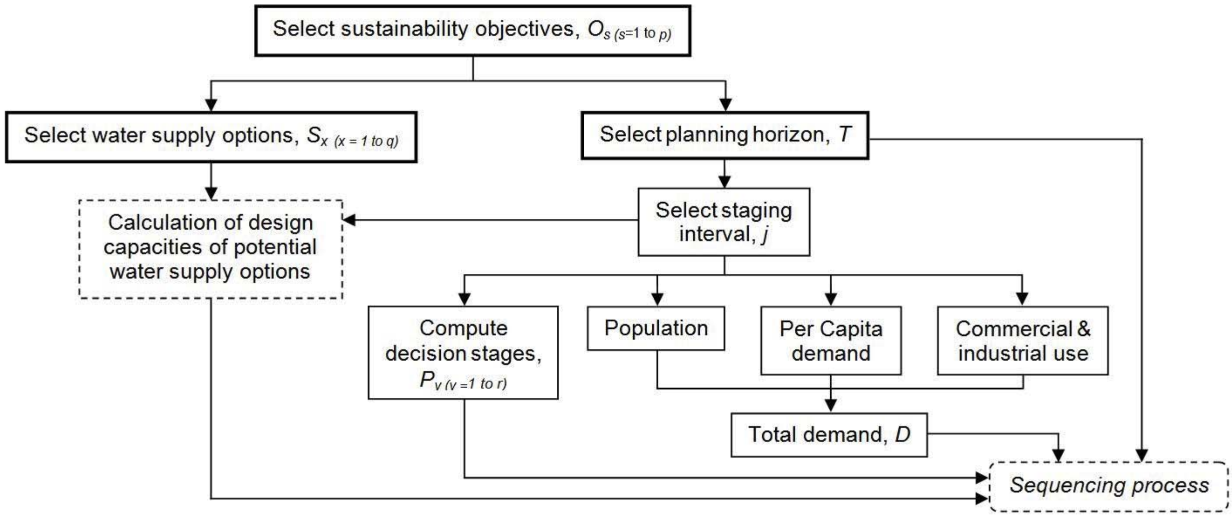

Figure 2.2 Steps in problem formulation process

Determining the objectives. The first issue to be addressed is the selection of the appropriate objective(s) O_s to be optimised during the development of the sequencing plans. The consideration of objectives other than cost minimisation, such as environmental and social objectives, is particularly important when non-traditional sources of water are being considered. For example, the production of desalinated water requires significantly more energy than collecting water from traditional sources, increasing environmental impact; and recycling wastewater and stormwater elicits a range of public and government responses in terms of water acceptability and public health considerations.

Which objectives should be considered is case study dependent. There are a number of studies related to the sequencing of water supply sources that mainly focus on minimising the economic cost of the water supply system (Becker and Yeh, 1974, Knudsen and Rosbjerg, 1977, Martin, 1987, Chung et al., 2009). Understanding the potential environmental and social impact of the supply system is a challenge, given the variety of parameters (e.g., energy usage) that must be considered, many of which are hard to quantify (Yurdusev and O'Connell, 2005).

Establishing a planning horizon and defining decision points. Next, the planning horizon T needs to be established. Determination of an appropriate planning period is crucial for sustainable water supply system planning. Mitchell *et al.* (2007) suggested the use of a 50 to 100 year planning timeframe in order to adequately account for the lifespan of water supply infrastructure. At the same time, the staging interval j (i.e., the length of time between decision points in the sequencing plan) needs to be selected. This interval should reflect a realistic period for the assessment of planning decisions and the design life of the supply options.

After the planning horizon and staging interval have been defined, the number of decision stages P_y can be computed by dividing the planning horizon by the staging interval. Information about the planning horizon, staging intervals and decision stages feeds into the sequencing process, as shown in Figure 2.2.

Defining demand. The demands at the various decision points P have to be defined. They are a function of the total population and per capita demand, as well as industrial and commercial demand. As population and demand are likely to change over time, they need to be calculated based on future projections. Projected demand over the planning period is used as a constraint in the optimal sequencing process (Section 2.2.3), as shown in Figure 2.2.

Selecting water supply sources. Finally, the potential water supply sources need to be defined for each staging interval. Potential options include traditional sources, such as groundwater, rivers, lakes and reservoirs, and alternative sources, such as stormwater harvesting, rainwater tanks, wastewater reuse and desalination.

In addition, cases where the expected lifespan of a potential supply source is shorter than the planning horizon, as might be the case for rainwater tanks, for example, also need to be identified. In such cases, parts of the infrastructure for the potential water sources might need to be replaced as part of the sequencing process.

2.2.2 Calculation Of Yield For Potential Water Supply Options

In order to develop optimal sequence plans, water supply options that optimise the objectives while satisfying the demands need to be selected. Consequently, the supply capacities of the available water sources need to be known at each decision stage.

Maximum capacities generally depend on a number of case study specific factors, such as water resources availability, including rainfall, river flow and groundwater yield; the storage capacity of aquifers for the harvesting of stormwater or extraction of groundwater; and geographical constraints that affect the locations of potential reservoirs. Some sources have a fixed yield (e.g., desalination). However, this is not the case for other sources, such as reservoirs, stormwater harvesting schemes and rainwater tanks, as their yields will vary from year to year as a result of hydrologic variability. In order to address this problem, the yield that can be achieved with a certain user-defined exceedance probability can be used as the design yield for rainfall dependent sources.

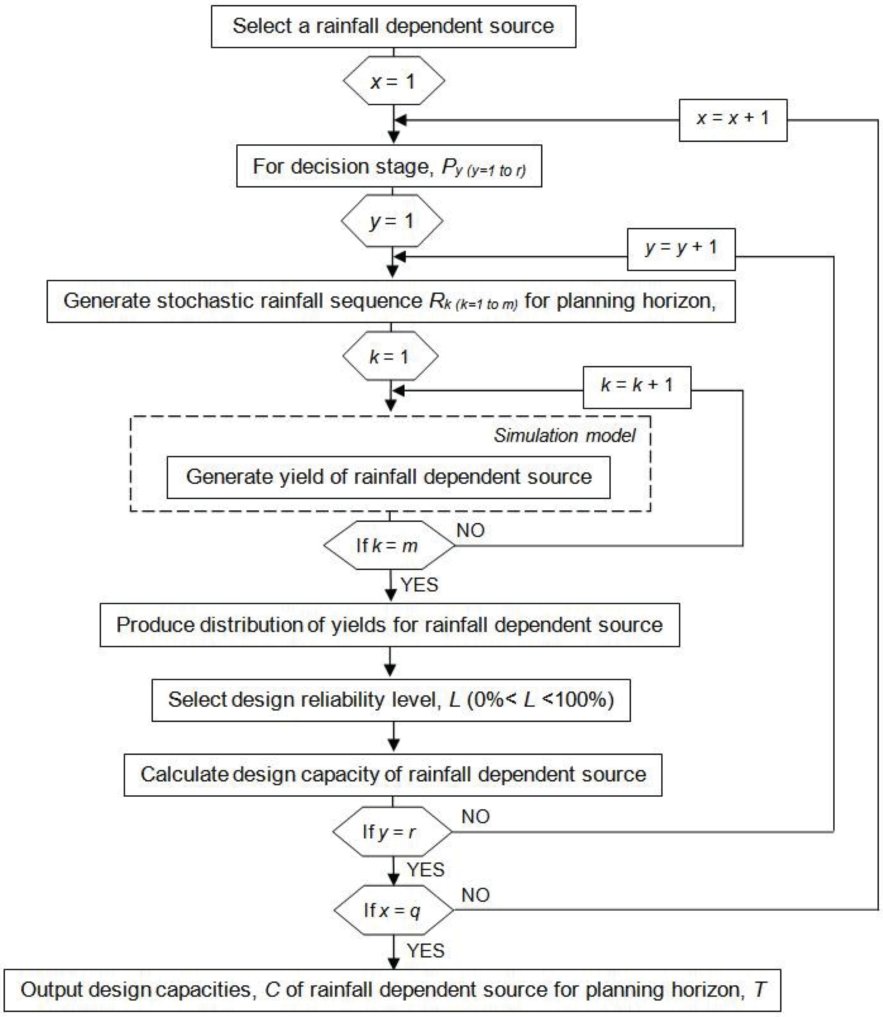

Figure 2.3 Process of calculating the yield of rainfall dependent source

The proposed procedure for calculating the yield for rainfall dependent water supply options is shown in Figure 2.3 and described below. Firstly, a rainfall dependent source (e.g., reservoir, rainwater tank) is selected. Then, a stochastic rainfall sequence of appropriate length R_1 is generated for the duration of P_1 in order to account for the natural variability in rainfall. This rainfall sequence, together with the projected demand, is then used as input to a simulation model of the selected potential water source, in order to obtain a time series of yield. The result is averaged in order to obtain an average annual yield for the selected source throughout the period P_1.

It should be noted that the yield of each source in the simulation is the maximum of the available capacities throughout the period P_1. By repeating the process of generating the yield of a rainfall dependent source for *m* stochastic rainfall sequences, a distribution of average annual yields is obtained for the selected source (Figure 2.3). Then, an appropriate design reliability level is selected. If the selected reliability level is 95% (i.e., there is a 95% probability that the yield is greater than or equal to the demand), the yield at the 95th percentile of the distribution is chosen as the design yield *C*. This process is then repeated for the *r* decision stages to generate the yields of the selected source for the planning horizon *T*. The process in Figure 2.3 is repeated for all rainfall dependent sources, and the calculated yields are then used as the constraints for the corresponding decision variables in the sequencing process (see Section 2.2.3).

2.2.3 Sequencing Process

The final component of the proposed approach involves the sequencing of the *i* potential water supply options along the planning horizon *T* by optimising the selected sustainability objectives O_S at all decision stages. For the sake of computational efficiency, an optimisation formulation that includes the entire solution space is not considered. Instead, two formulations that represent different approximations to the overall optimisation problem are proposed, including the 'build up' (BU) and 'build to target' (BTT) methods (Dandy et al., 2002).

In both methods, optimal sequence plans are developed for all staging intervals at the beginning of the planning horizon, based on the best possible projections of factors affecting objective function values (e.g. costs, energy usage etc.) and constraints (e.g. demands). In the BU method, plans are optimised in chronological order, operating on one decision stage P_y after another. Decisions made at previous stages remain fixed at subsequent stages, which means that the water supply options and capacities selected in the early stages will remain part of the system throughout the rest of the planning horizon. In contrast, in the BTT method, the sequence plans are first optimised for the target year (i.e., final decision stage). Then, a series of sub-problems is optimised, one for each intermediate decision stage, to identify when each water supply option selected in the target year should be implemented, starting with the initial planning stage and working forwards in time. It is a feature of BTT, therefore, that since all the water options for the target year are identified first, the optimisation at each decision stage must necessarily be constrained by those decisions. An advantage of the BU method is that it is more flexible and responsive to future changes, such as reductions in the growth of demand. However, it also generally results in less favourable objective function values compared with those obtained using the BTT method for the selected design conditions, which is a disadvantage if the assumed design conditions actually occur.

It is proposed to solve the BU and BTT sequencing problem formulations using mixed integer linear programming (LP), as it is computationally efficient (Loucks et al., 1981), and has been used successfully in previous water resources expansion studies (e.g., (Hsu et al., 2008) and (Han et al., 2011). In order to account for multiple, competing objectives, it is proposed to use the weighted sum method (Rangaiah, 2009), as it has been used extensively for this purpose in previous studies (Tolson et al., 2004). The method transforms multiple objectives into an aggregated objective function by multiplying each objective function by a weighting factor and summing up all weighted objective functions:

$$\boldsymbol{O_{weigted\ sum}} = \boldsymbol{w_1 O_1} + \boldsymbol{w_2 O_2} + \cdots + \boldsymbol{w_p O_p}$$

(2.1)

where w_s is a weighting factor for the s^{th} objective function. It should be noted that the values of the weighting factors range from 0 to 1, and that the sum of the weighting factors should equal 1. The values of w_s depend on the relative importance of each objective in the context of the problem. However, the optimisation problem can be solved repeatedly with different combinations of weights in order to obtain different solutions that are Pareto optimal (i.e. solutions for which an improvement in one objective results in the deterioration of at least one of the other objectives) (Tolson et al., 2004).

The detailed formulations of the BU and BTT methods are given in the subsequent sections.

2.2.3.1 BU Method

The proposed process of optimal sequencing using the BU method is shown in Figure 2.4. Firstly, weighting factors w_s are selected for each of the sustainability objectives (Figure 2.4). Then, an optimal sequence plan is generated by mixed integer LP in order to select a water supply sequence that optimises the sum of the standardized values of the objective function given in (2.2). Afterwards, water supply options that are already part of the water supply system under investigation need to be identified (e.g. existing water supply sources that are in service). Next, the values of the decision variables (i.e., potential water supply sources to be included and their capacities) are selected for the first decision stage P_1, so that the resulting combination of existing and selected potential water supply options optimises the objective function (2.2) while satisfying constraints (2.3) to (2.6).

$$Maximize\ benefit,\ z = \sum_{s=1}^{p} w_s \left[\sum_{y=1}^{r} \sum_{x=1}^{q} \left(B_{xy} K_{xys} + Q_{xy} P_{xys} \right) \right]$$

(2.2)

subject to

$$\sum_{s=1}^{p} w_s = 1$$

(2.3)

$$B_{xy} = \begin{cases} 1, & \text{if water supply option } x \text{ is built at decision stage } y \\ 0, & otherwise \end{cases}$$

(2.4)

$$Q_{xy} \leq B_{xy}C_x$$

(2.5)

$$\sum_{x=1}^{q} (Q_{xy}) \geq D_y$$

(2.6)

where

K_{xys} = capital value of objective function s of water supply options x at decision stage y

(2.7)

P_{xys} = operating value of objective function s of water supply options x at decision stage y

(2.8)

and

Q_{xy} = supply volume for water supply option x at decision stage y

(2.9)

The objective function O_s consists of capital and operating values of each of the selected objectives. The capital values K are a function of the integer variable B; and the operating values P are a function of supply capacity Q. Decision variable Q_{xy} represents the supply volume for water supply option x at decision stage y, and Q_{xy} have to be equal to or less than the yield of the selected water supply option at decision stage y, $B_{xy}C_x$ (2.5). Furthermore, for the total supply volume for the selected water supply option at decision stage y, Q_{xy} has to be greater than or equal to the demand at decision stage D_y (2.6).

Subsequently, the list of existing water supply options is updated with the options selected during this decision stage. The process of selecting the most appropriate values of the decision variables and updating the list of existing water supply options is repeated for r decision stages (Figure 2.4). Then, the optimised objective function values are summed over the q water supply options and r decision stages, and computed for the selected sustainability objectives O_s to generate optimal sequence plans.

The BU method involves firstly solving the optimisation problem for the initial decision stage. Then each subsequent stage is optimised with the decisions from the previous stages locked in place.

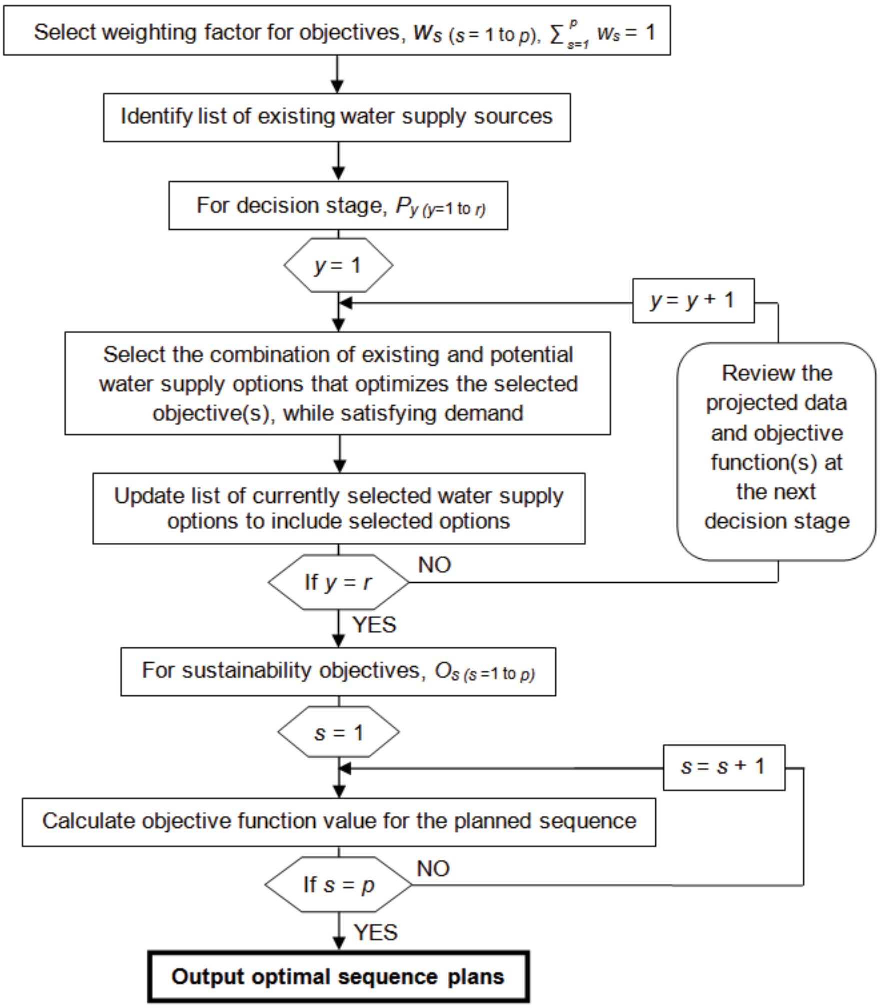

Figure 2.4 Sequencing process by the BU method

2.2.3.2 BTT Method

The proposed sequencing process using the BTT method is shown in Figure 2.5. On a similar way to the BU method, weighting factors for the sustainability objectives O_s are chosen at the first step, followed by the identification of the current water supply options (Figure 2.5). Then, a combination of water supply options *u* is selected to meet the demand at the final decision stage *r* by optimising the objective function (2.10) while satisfying constraints (2.11) to (2.14).

$$Maximize\ benefit,\ z = \sum_{s=1}^{p} w_s \left[\sum_{x=1}^{q} (B_x K_{xs} + Q_x P_{xs}) \right]$$

(2.10)

subject to

$$\sum_{s=1}^{p} w_s = 1$$

(2.11)

$$B_{xy} = \begin{cases} 1, & \text{if water supply option } x \text{ is built at decision stage } y \\ 0, & \text{otherwise} \end{cases}$$

(2.12)

$$Q_x \leq B_x C_x$$

(2.13)

$$\sum_{x=1}^{q} (Q_x) \geq D$$

(2.14)

where

$$K_{xs} = \text{capital value of objective function } s \text{ of water supply options } x$$

(2.15)

$$P_{xs} = \text{operating value of objective function } s \text{ of water supply options } x$$

(2.16)

and

$$Q_x = \text{supply volume for water supply option } x$$

(2.17)

Next, this set of water supply options *u* is scheduled to meet demand by optimising the selected sustainability objectives starting with the first decision stage by using the BU method (2.2), while satisfying constraints (2.3) to (2.6). Similar to the BU method, the list of scheduled water supply options is then updated for each decision stage. Subsequently, the total objective function values are computed for the selected sustainability objectives, and then the optimal sequence plans are generated (Figure 2.5).

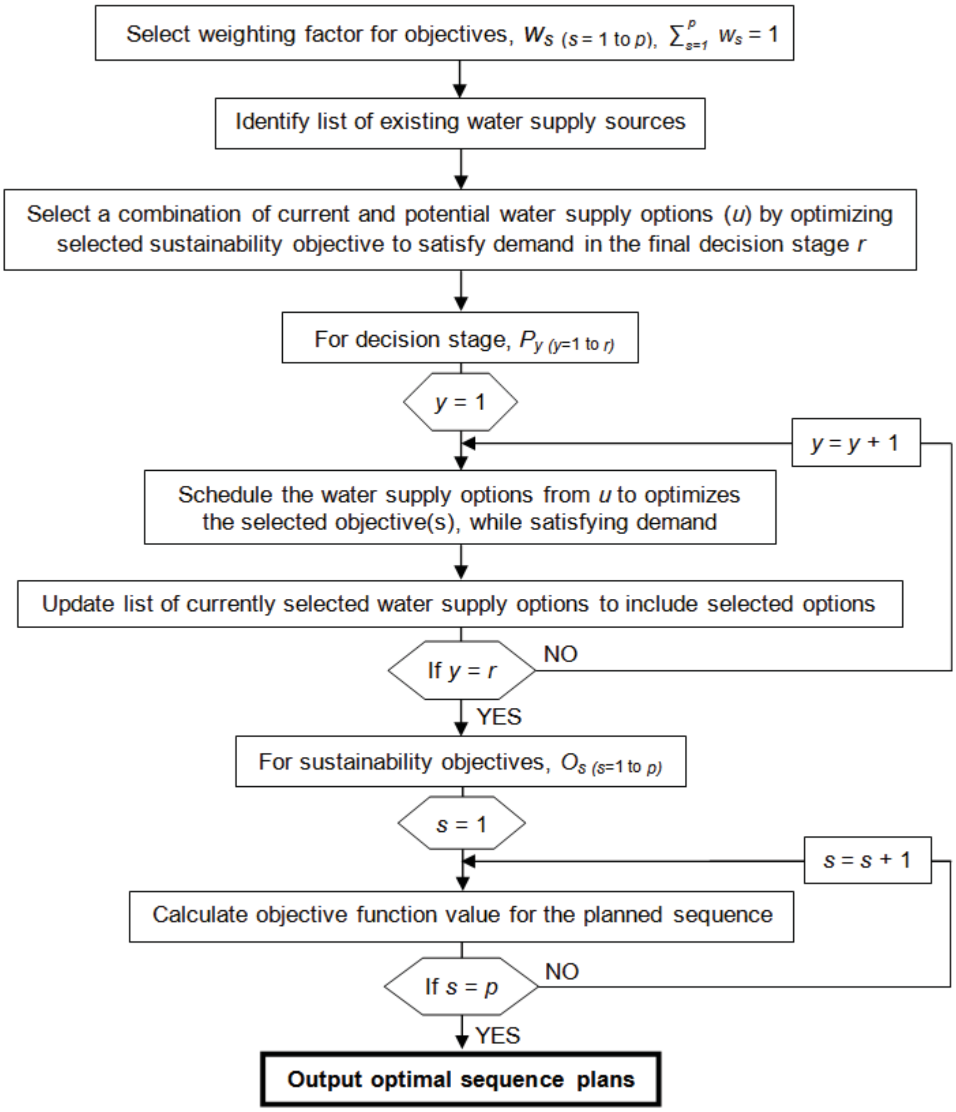

Figure 2.5 Sequencing process by the BTT method

For the BTT method, only the combination of sources u, which were selected to meet the demand in the final year, are available for selection when scheduling the water supply options from stage to stage using the BU method. So, the optimisation problem is smaller as the run times for the scheduling of water supply options will be much shorter. Additionally, the optimal sequence plan is generated for the final year, which generally involves less infrastructure duplication during the planning horizon T.

2.3 Case Study

In order to illustrate the proposed sequencing methods and assess their utility, they are applied to a case study based on the southern portion of the Adelaide water supply headworks system. Adelaide is the capital city of South Australia (see Figure 2.6) 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. Recorded annual rainfall ranges from 257mm to 882mm (Maier et al., 2013).

The average annual mains water consumption is estimated to be 150 gigalitres (GL), but the demand has ranged from 140GL/year to 200GL/year over the last 10 years depending on the prevailing weather patterns (Government of South Australia, 2005).

The southern Adelaide water supply system (WSS) (see Figure 2.6) supplies around 50% of the demand of metropolitan Adelaide (Paton et al., 2013). The system consists of three reservoirs – Myponga, Mount Bold and Happy Valley. Mount Bold reservoir, with a capacity of 46.2GL, is the largest reservoir in South Australia. It receives runoff from a 388km^2 catchment and supplementary water from the River Murray via the Murray Bridge-Onkaparinga pipeline (Crawley, 1995). The pipeline discharges water from the River Murray directly into the Onkaparinga River near the town of Hahndorf, from where it is channelled 10km downstream to Mount Bold reservoir. The pipeline can supply up to 514ML per day.

Mount Bold reservoir is not directly connected to the distribution system, and is considered to be a storage reservoir. Controlled releases from the reservoir flow along the Onkaparinga River to Clarendon Weir, where the water is diverted to Happy Valley reservoir via the Happy Valley diversion tunnel. Happy Valley reservoir also collects water from its own 54km^2 catchment, located downstream of Mount Bold reservoir, but upstream of Clarendon Weir. Water is captured in Happy Valley reservoir providing the capacity of the Happy Valley reservoir diversion tunnel is not exceeded (Crawley, 1995). Water directed from Happy Valley reservoir is treated at the Happy Valley water treatment plant before being supplied to the Adelaide southern region through a series of pipelines. The filtration plant has a capacity of 850 megalitres (ML) per day (SA Water, 2012b).

Myponga reservoir, with a capacity of 26.8GL, is vital for water storage and water supply to the southern Adelaide region, as well as to a number of small towns to the south of the city. There are no inter-catchment transfers to the reservoir and it is entirely fed by the Myponga River catchment with an area of 124 km^2, and thus the inflow to the reservoir is wholly dependent on rainfall. The reservoir has an average yield of 15GL per year, which is 10% of Adelaide’s water supply (Thomas et al., 1999). Water from Myponga reservoir is treated at the Myponga water treatment plant, which has a capacity of 50ML per day (SA Water, 2012b).

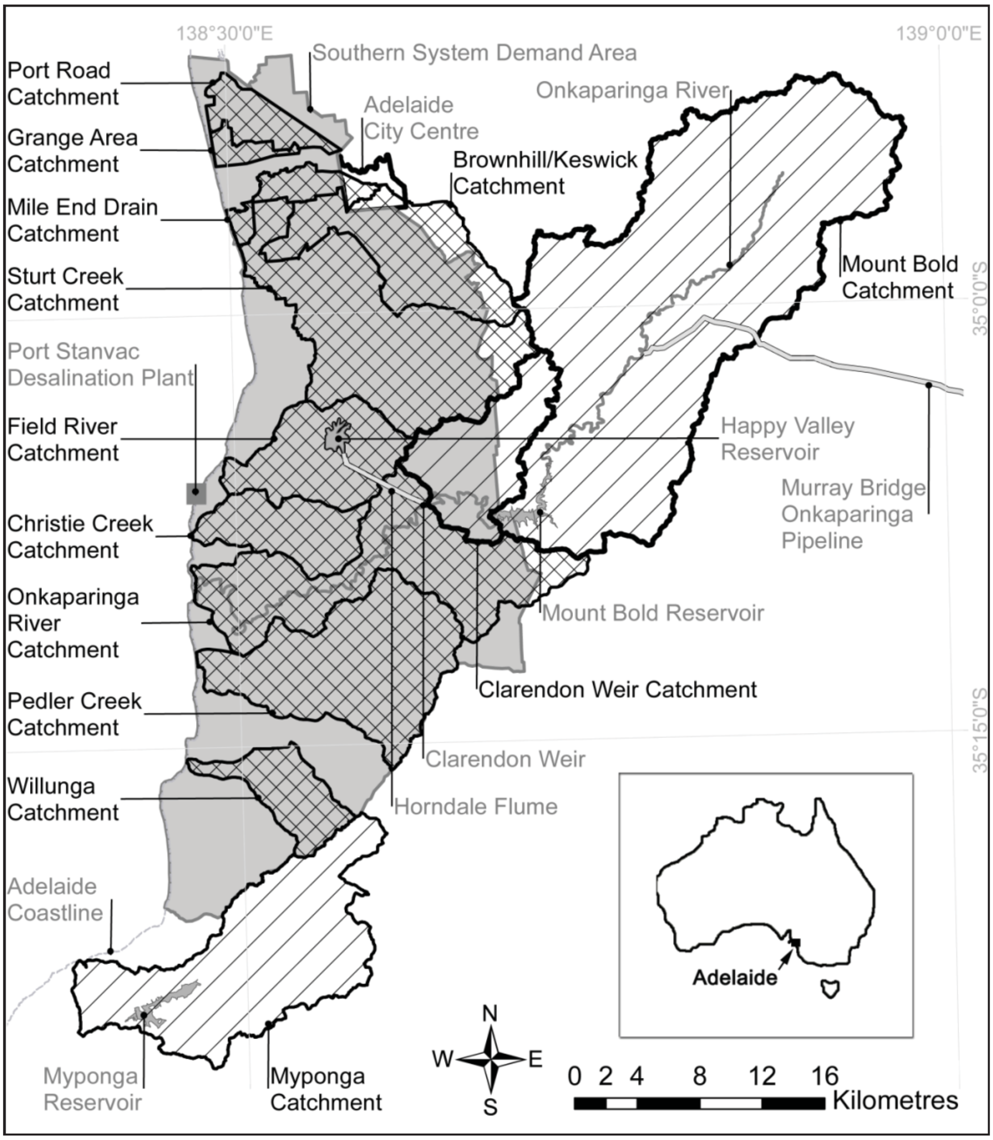

Figure 2.6 The southern Adelaide water supply system.

The application of the proposed sequencing approaches to the case study based on the southern Adelaide water supply system is presented in the following sections.

2.3.1 Problem Formulation

Determining the objectives. Increasing awareness of the desirability of reducing the environmental impact associated with water resources development has resulted in more studies in which GHG emissions are considered. These are of particular concern for the southern Adelaide system, as a result of a large amount of pumping and the consideration of desalination as an alternative source of water. The objectives for the case study therefore include economic cost and GHG emissions. The function values of the objectives (i.e., cost and GHG emissions) are categorised as capital and operating. Capital objective function values are incurred during the construction phase of a project (e.g., materials and outlay), whilst operating objective function values are incurred over the life of a project (e.g., maintenance and electricity for pumping).

Establishing a planning horizon and defining decision points. A planning horizon of 40 years (from 2010 to 2050) is used, to correspond with the Water for Good plan, which considers SA's water supply security to 2050 (Government of South Australia, 2009b). A staging interval of five years is adopted, as five years is a practical period for review from a planning perspective. Therefore, the case study includes eight decision stages over the 40 year planning horizon. This time period allows for the review of the plans in light of changing exogenous variables, such as rainfall, demand and costs.

Defining demand. Of particular importance to decisions made at each stage is the estimation of total demand D, which is a function of population size, per capita demand and commercial and industrial demand (see Figure 2.2). The population for the southern Adelaide region was estimated to be 598,600 in 2010 (Australia Bureau of Statistics, 2011) and a population growth rate of 0.74% per annum is assumed over the 40 year planning horizon. The average household size is assumed to be constant at 2.3 people. Average daily demand was taken as 494litres (L) per capita in 2010 (Government of South Australia, 2009b). This includes water use for industrial, commercial, primary production and public purposes (ICPP). However, as a result of planned water reduction measures by the SA government, annual percentage reductions in demand corresponding to the values in Table 2.1 are used based on the Water for Good plan (2009b). Detailed justification of the values adopted in relation to estimating demand over the selected planning horizon is provided in the supplementary material.

Table 2.1 Annual demand and reduction for the southern Adelaide water supply system

Demand category	Annual demand in 2010	Annual reduction in per capita demand
Residential I (drinking, bathing and laundry)	40.82GL	0.24%
Residential II (toilet flushing and garden watering)	27.22GL	0.61%
Industrial, commercial, primary production and public purposes (ICPP)	39.96GL	0.28%

Selecting water supply sources. For the case study, the existing water supply options (i.e., Happy Valley reservoir, Myponga reservoir and the River Murray) are included in the sequencing plan at the beginning of the planning horizon. However, a desalination plant, stormwater harvesting schemes and household rainwater tanks are considered as potential additional water supply sources at each decision stage during the planning horizon. Stormwater and rainwater are not suitable for potable use (Residential I) and are therefore assigned to non-potable uses. The proportions of potable and non-potable demands for the southern Adelaide WSS are given in Table 2.1. Supply from the reservoirs and the desalination plant are chosen to provide Residential I demand. The stormwater harvesting schemes can supply 30% of the ICPP demand as non-potable water; and rainwater tanks are used as the first option for the supply of Residential II demand. When the supply from the stormwater harvesting schemes and rainwater is insufficient, potable supply from reservoirs and the desalination plant is used to supply the Residential II and ICPP demand.

A reverse osmosis (RO) desalination plant with an annual capacity of either of 50GL or 100GL is considered as a potential water supply option for the case study, with an option of expanding the 50GL desalination plant 100GL annual capacity if required at a later stage, which is in line with proposals made by the South Australian government to ensure potable water supplies, even in times of drought (Government of South Australia, 2009b). The location of the plant is at Port Stanvac (see Figure 2.6). As part of the system, desalinated water is pumped through a pipeline to Happy Valley reservoir, where it is combined with water from the water treatment plant before entering the existing water supply network (SA Water, 2012a). It should be noted that the capacity of the desalination plants is halved for the case study because they are designed to supply the whole of metropolitan Adelaide. The southern system featured in the case study, therefore, only takes 50% of the supply.

Within the southern Adelaide demand area, there are ten potential stormwater harvesting schemes that could be implemented in the future and are considered in this study: Brownhill- Keswick, Grange Area, Port Road, Mile End Drain, Sturt River, Field River, Christie Creek, Onkaparinga River, Pedler Creek and Willunga (Wallbridge & Gilbert, 2009) (Figure 2.6). As estimated by Wallbridge & Gilbert (Wallbridge & Gilbert, 2009), these schemes have a total annual potential yield of 22GL, subject to rainfall. The amount of water that can be harvested from each scheme depends on the runoff from the catchment, the injection rate and the discharge rate for the wetlands and aquifers. Due to insufficient good quality aquifer storage within the southern Adelaide region, it is proposed that the runoff from Christie Creek and Onkaparinga River be diverted to the Pedler Creek scheme's storage after treatment via wetlands (Wallbridge & Gilbert, 2009). Therefore, supply from Christie Creek, Onkaparinga River and Pedler Creek are combined for the case study. Similarly, four of the catchments (Grange Area, Port Road, Mile End Drain and Willunga) are ungauged, so they are assigned similar characteristics as nearby catchments (i.e. the same calibration parameters) and for simplicity have been amalgamated with these catchments. Specifically, Grange Area, Port Road and Mile End Drain are combined with Brownhill-Keswick, while Willunga is combined with Pedler Creek (Figure 2.6).

Domestic household rainwater tanks are also included in the case study as potential water supply options. Four sizes of household rainwater tanks (1kL, 2kL, 5k and 10kL) are considered. It is assumed that, if a rainwater tank option is chosen, all houses will be required to install a tank of the specified size by a government regulation.

2.3.2 Calculation Of Yield For Potential Water Supply Options

The design yields of the different potential water supply sources, including the three reservoirs, the River Murray, the desalination plants, the stormwater harvesting schemes and rainwater tanks of four different sizes, are required in order to undertake the optimal sequencing process. It should be noted that although the three reservoirs and the River Murray are not considered as part of the sequencing process, as they are existing sources, their yields need to be included to ensure that optimal sequence plans that satisfy projected demands can be developed. As the yield from the desalination plant is independent of rainfall, the annual yields of the desalination plant are known and considered to be 50 and 100 GL, as discussed previously. However, the yields of the other potential sources need to be determined using the procedure outlined in Section 2.2.2.

1000 sequences of 40 years of daily stochastic rainfall data were generated for eight rainfall sites within the southern Adelaide WSS using the Stochastic Climate Library (SCL) (www.toolkit.net.au/scl). The methodology to develop stochastic rainfall time series applied by Paton et al.(2013) is also applied in this case study. The 1000, 40 year stochastic rainfall sequences are used as inputs to *WaterCress* (Water-Community Resource Evaluation and Simulation System) (WaterSelect, 2011) simulation models of the various rainfall dependent sources in order to generate a distribution of their yields. The performance of the *WaterCress* models during calibration and validation was assessed using graphical and analytical approaches (Bennett et al., 2013), as detailed in the supplementary material. These approaches include time series and scatter plots of actual and predicted values and the Nash Sutcliffe (NS) coefficient. See Bennett et al. (Bennett et al., 2013), for a review of approaches for characterising model performance.

Attention is drawn to the fact that the yields of the rainfall dependent sources are generated simultaneously in *WaterCress* to incorporate the interaction between stormwater harvesting schemes and rainwater tanks, because rainwater harvesting affects stormwater runoff from the impervious area of the catchment. The yield that corresponds to a probability of exceedance of 90% is determined for each source. *WaterCress* is used as the simulation model because of its ability to simulate a system containing reservoirs, stormwater harvesting schemes and rainwater tanks (Clark et al., 2002) and because it was developed specifically for South Australian conditions (WaterSelect, 2011).

The average annual supply from the River Murray to the metropolitan Adelaide water supply system was 109GL from 2002 to 2006 (SA Water, 2007), but it is anticipated that by 2020 the salinity of the water will make it unsuitable for potable use for 40% of the time (Conservation Council of South Australia, 2008). Hence, for the case study, supply from the River Murray is limited to 60% of the current average amount. The total supply is assumed to be evenly distributed between the northern and southern Adelaide systems (Crawley, 1995). The River Murray yield is generated using *WaterCress* with 1000 sequences of stochastic rainfall data, and the annual supply from the River Murray is determined as 24.4GL for the southern system due to the restrictions imposed by the water quality issues mentioned above.

For stormwater harvesting schemes, the yield is dependent on the total impervious and pervious areas of catchments, wetland capacity, injection rate and discharge rate for the wetlands and aquifers. Thus, these factors are important for the simulation model in order to generate the yields for each scheme.

For impervious catchments, daily runoff is calculated by multiplying the effective area, which is the total connected impervious area, by the runoff depth. For the pervious catchments, rainfall runoff (RRO) models are developed for the stormwater harvesting schemes, as detailed in the supplementary material. In order to calculate the yield of the household rainwater tanks, the number of dwellings, roof size and the fraction of roof connected to rainwater tanks had to be estimated. The number of dwellings considered in the case study is based on the estimated population growth and an average occupancy of 2.3 people per dwelling over the coming 40 years, as discussed previously. The 30 Year Plan for Greater Adelaide (2010) states that the region will move to a sustainable housing density, with a gross density of 25-35 dwellings per hectare of land for the metropolitan area. This includes infrastructure and non-residential development, and is categorized as medium residential density (Government of South Australia, 2006). According to Wallbridge and Gilbert (2009), the roof area for a medium density residential development can be assumed to be 250m^2, with 50% connected to household rainwater tanks.

Based on the outcomes of the above analyses, the following yields are generated for the selected rainfall dependent water supply options (Table 2.2) for the sequencing process.

Table 2.2 Yields for the selected water supply options

Water supply option	Annual Yields (90% reliability)			
Happy Valley/ Mt Bold reservoirs	50.3 GL			
Myponga reservoir	6.4 GL			
River Murray	24.4 GL			
Stormwater harvesting schemes	Brownhill-Keswick	Sturt River	Field River	Pedler Creek
	6.3 GL	7.0 GL	1.6 GL	5.0 GL
Household rainwater tanks	1kL	2kL	5kL	10kL
	9.1 GL (35.0 kL/tank)	11.1 GL (42.8 kL/tank)	12.2 GL (46.8 kL/tank)	12.3 GL (47.1 kL/tank)

2.3.3 Sequencing Process

As mentioned in Section 2.2.3, the first step in the sequencing process is to assign a weighting factor w_s to the selected objectives, including (in this instance) economic cost and GHG emissions from the construction and operation of the water supply options. Weighting factors of w_1 = 1.0 and w_2 = 0; w_1 = 0 and w_2 = 1.0; and w_1 = 0.5 and w_2 = 0.5 are used for the case study in order to investigate the impact on the optimal sequencing plans and objective function values of considering only the economic objective, only the greenhouse gas objective and assigning equal consideration to both objectives.

Economic costs and GHG emissions are commonly divided into two types: capital and operating. Capital values are incurred during the construction phase of a project (e.g., costs of material and outlay); whilst operating values are incurred over the life of a project (e.g., electricity for operation, maintenance, and upgrades). It is assumed that all initial capital values are incurred at the project start date. Additionally, the capital emissions values in the case study are computed using embodied energy (Treloar, 1995) and emission factor analysis (Wu et al., 2010b).

The majority of the operating costs and GHG emissions are due to energy usage associated with pumping, especially for the desalination plant. Therefore, there is a cost factor related to the electricity for running the pumps, and a different cost factor for GHG emissions related to the generation of electricity. SAWater's estimated average price of electricity for the financial year ending June 2010 is 10c/kWh (SA Water, 2010). However, electricity costs are projected to increase in South Australia, and a conservative indicative cost of 12c/kWh is assumed for the electricity price. The electricity GHG emission factor is assumed to be 0.81kgCO_2-e/kWh. This factor is the full fuel cycle emission factor estimate for electricity purchased by South Australian end users (Australian Government, 2011a).

Additionally, the design life of different infrastructure components is incorporated into the case study by assuming that each component would be replaced at the same capital cost and capital GHG emissions. For the purposes of this study, water supply options are assumed to remain in place and to continue to be maintained for the rest of the planning horizon once they had been introduced. The design lives of the infrastructure used in the case study for the various water supply options is given in Table 2.3.

Table 2.3 Design lives for the components of various water supply options

Components of water supply options	Design life (years)	Source of information
Water treatment plant	50	(Baruth, 2005)
Mechanical parts for water treatment plants	7	(Baruth, 2005)
Pumps (Desalination plant & water treatment plant)	20	(Water Services Association of Australia, 2002)
Pumps (Household rainwater tanks)	15	Assumed
HDPE household rainwater tanks	20	(Polytank Sales and Service, 2011)
Membranes for RO desalination plant	5	(Lawler et al., 2011)

During the optimal sequencing process, the supply capacity assigned to each selected water supply option is chosen in order to optimise the weighted cost and GHG emissions to generate optimal sequence plans, as given in (2.2) for the BU method and (2.10) for the BTT method. The supply capacities of the selected water supply options cannot exceed the yields (see Table 2.2) as illustrated in (2.5) for the BU method and (2.12) for the BTT method. It should be noted that the full capacity of each water supply options is not necessarily used and the supply taken could vary from stage to stage based on demand and supply from the mixture of selected supply options. Additionally, the total supply from all selected water supply options is to meet the total demand at each decision stage, as given in (2.6) for the BU method and (2.13) for the BTT method.

The capital and indicative operating costs and GHG emissions of the potential water supply sources are given in Table 2.4. In calculating these values, it is assumed that all capital values are incurred at the project start date. Additionally, the capital emissions values are computed using embodied energy (Treloar, 1995) and emission factor analysis (Wu et al., 2010b). However, the majority of the operating costs and GHG emissions are due to energy usage associated with pumping, especially for the desalination plant and the River Murray. Additionally, operating cost and GHG emissions are a function of total supply from selected water sources, and the corresponding unit operating objective function values. The estimated values of unit operating costs and GHG emissions based on the yields for 90% reliability are given in Table 2.4. Details of the cost and GHG emission calculations are given in the supplementary material.

It should be noted that the costs associated with the measures that are assumed to result in demand reduction over time (e.g. adoption of low-flow showerheads, installation of dual-flush toilets etc.) are not included in the analysis as they are the same for all potential sequence plans and therefore do not have an impact on the selection of the optimal sequences.

Table 2.4 Capital and operating cost and GHG emissions for the various water supply options

Water supply options	Yield	Capital cost ($)	Unit operating cost ($/kL)	Capital GHG emissions ($kgCO_2$-e)	Unit GHG emissions ($kgCO_2$-e/kL)
Happy Valley reservoir	50.3 GL/year	-	0.03	-	0.24
Myponga reservoir	6.4 GL/year	-	0.23	-	0.22
River Murray	24.4 GL/year	-	0.44	-	2.93
50GL desalination plant	25.0 GL/year	1,347,000,000	1.00	228,538,259	5.41
100GL desalination plant	50.0 GL/year	1,830,000,000	1.00	237,103,259	5.43
50GL desalination expansion	25.0 GL/year	483,000,000	1.00	8,565,000	5.41
Stormwater harvesting schemes :					
Brownhill & Keswick Creek	6.3 GL/year	160,025,000	1.23	7,248,734	2.04
Sturt River	7.0 GL/year	194,193,000	1.23	7,350,767	2.06
Field River	1.6 GL/year	35,689,000	1.23	3,576,467	6.05
Pedler Creek	5.0 GL/year	110,682,000	1.23	5,643,330	1.60
Household rainwater tanks:					
1kL	35.0 kL/tank/year	2,181	0.78	718	1.22
2kL	42.8 kL/tank/year	2,464	0.68	1,251	1.22
5kL	46.8 kL/tank/year	3,024	0.64	2,897	1.22
10kL	47.1 kL/tank/year	3,560	0.63	4,635	1.22

Discounting of future operating costs and GHG emissions is taken into account with an appropriate present value analysis and discount rate for a particular system. The present value (PV) of future capital costs and GHG emissions can be evaluated using the following discounting equation (Dandy et al., 2007):

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

(2.18)

where, *F* are the future costs or GHG emissions incurred; *t* is the future time period, and *i* is the discount rate used. The present value of constant annual operating costs can be expressed as:

$$PV = \frac{A \times [1-(1+i)]^n}{i}$$

(2.19)

where, *A* is the periodic total annual operating costs or GHG emissions of a project; *n* is the number of time periods; and *i* is the discount rate used. In this study, an economic discount rate of 6% is used, as discount rates around 6-8% are commonly used for capital works (Wu et al., 2010a). In contrast, a discount rate of 1.4% is used for GHG emissions, as this has been suggested as appropriate for stabilizing GHG concentrations in the atmosphere within a desired range (Wu et al., 2010b).

2.4 Analyses Conducted

As mentioned in Section 2.3, for each of the two sequencing methods considered (i.e., BU and BTT), three optimal sequence plans are developed, each with different weightings of the cost and GHG emission reduction objectives (i.e., w_1 = 1.0 and w_2 = 0; w_1 = 0.5 and w_2 = 0.5; and w_1 = 0 and w_2 = 1.0) (see Section 2.3.3). In addition, a number of scenarios are conducted in order to assess the sensitivity of the objective function values (i.e., costs and GHG emissions) and solutions (i.e., optimal sequence plans) to uncertain conditions and to assess the differences in objective function values and solutions obtained using the BU and BTT sequencing approaches under these conditions. The uncertain conditions considered in the scenario analysis include the available supply from the River Murray and population growth, both of which will have a major impact on supply or demand, as well as discount rate. The three factors investigated can have a significant impact on the resulting optimal sequencing plans.

The annual supply from the River Murray is restricted to 24.4GL by considering the water quality for the base case scenario (see Section 2.3.2). Supply is, however, likely to be greater than this, especially in summer when the river supplies 90% of Adelaide's demand (Government of South Australia, 2009b). Thus, the annual River Murray supply is increased to comply with the current 5-year rolling license for Adelaide, of which half is allocated to the southern Adelaide WSS), with the yield at 90th percentile of

51.3GL/year in one of the scenarios investigated in order to assess the impact of these supply changes on the schedules of the water supply options implemented in the optimal sequence plans (see Table 2.5).

Table 2.5 Details of scenario analysis conducted

Scenario	River Murray yield (GL/year)	Population growth rate (per annum)	Economic discount rate (per annum)	GHG emission discount rate (per annum)
Base case (S1)	24.4	0.74%	6%	1.4%
Increased River Murray supply (S2)	51.3	0.74%	6%	1.4%
Low population growth (S3)	24.4	-0.68%	6%	1.4%
High population growth (S4)	24.4	1.58%	6%	1.4%
Low discount rates (S5)	24.4	0.74%	4%	0%
High discount rates (S6)	24.4	0.74%	8%	3%

As mentioned in Section 2.3.1, there are 72 different population projections for Adelaide, which are based on a number of assumptions of fertility, mortality, net interstate migration and net overseas migration (Australia Bureau of Statistics, 2008). The annual linear population growth rate that corresponds to the 50th percentile of these projections (i.e. 0.74%) is used as the base case, as stated in Section 2.3.1. In addition, low (-0.68%) and high (1.58%) annual linear population growth scenarios are considered (Table 2.5), which correspond to the 5th and 95th percentile of the 72 population projections, respectively (Australia Bureau of Statistics, 2008). The projected annual demands used at each decision stage in the sequencing process for the base case, low population and high population scenarios are given in Table 2.6.

The selection of appropriate discount rates is critical because they have a major impact on the present value of future economic costs and GHG emissions. However, there is no clear consensus in relation to which discount rate should be used and a wide range of values has been suggested in the literature. In relation to economic discount rates, values of 2% to 4% were recommended by Simpson (2008) for the assessment of water supply systems. However, this is lower than the rate of 6% to 8% commonly used for capital works projects (Wu et al., 2010b). As mentioned in Section 2.3.1, an economic discount rate of 6% is used as the base case. In addition, economic discount rates of 4% and 8% are considered in the scenario analysis (Table 2.5). In relation to GHG emission discount rates, suggestions range from 0%, as in the Intergovernmental Panel on Climate Change's Second Assessment Report (Fearnside, 2002), to using the same discount rate as for money (Van Kooten et al., 1997). As mentioned in Section

2.3.1, a GHG emission discount rate of 1.4% is used as the base case. In addition, GHG emission discount rates of 0% and 3% are considered in the scenario analysis. Overall, high (8% economic discount rate, 3% GHG emission discount rate) and low (4% economic discount rate, 0% GHG emission discount rate) discount rate scenarios are considered in addition to the base case discount rates (6% economic discount rate, 1.4% GHG emission discount rate) (Table 2.5).

In summary, low and high population scenarios, as well as low and high discount rate scenarios, are considered in addition to the base case (Table 2.5). For each of these six scenarios, optimal sequence plans are obtained using the BU and BTT methods, each with three sets of objective function weightings (i.e., w_1 = 1.0 and w_2 = 0; w_1 = 0.5 and w_2 = 0.5; and w_1 = 0 and w_2 = 1.0). Consequently, 36 optimal sequence plans are developed in total.

Table 2.6 Projected annual demands at each decision stage for three scenarios considered in the analyses

Decision stage	Demands for base case scenario (GL)			Demands for low population scenario (GL)			Demands for high population scenario (GL)		
	Residential I	Residential II	ICPP	Residential I	Residential II	ICPP	Residential I	Residential II	ICPP
2010	70.42	12.26	27.36	67.69	11.78	26.30	73.28	12.75	28.48
2015	71.98	12.51	27.45	66.59	11.57	25.40	77.63	13.49	29.61
2020	73.47	12.75	27.48	65.49	11.37	24.49	81.84	14.21	30.61
2025	74.90	12.98	27.44	64.40	11.16	23.60	85.91	14.89	31.48
2030	76.27	13.20	27.35	63.32	10.96	22.71	89.84	15.55	32.22
2035	77.57	13.41	27.19	62.24	10.76	21.82	93.64	16.19	32.83
2040	78.81	13.60	26.98	61.17	10.56	20.94	97.29	16.79	33.31
2045	79.98	13.78	26.70	60.11	10.36	20.07	100.81	17.37	33.66

2.5 Results and Discussion

The optimal sequence plans for the different scenarios, optimisation methods and objective function weightings considered are given in Table 2.7 and the corresponding values of the optimal costs and GHG emissions are shown in Table 2.8. In Table 2.7, a'1' means that the project is implemented in first decision stage (i.e., 2010) and a '2' means implemented in 2015 and so forth. It should be noted that results for the low- and high- discount rate scenarios are not given in Table 2.7, as in this case, the optimal schedules are not affected by discount rates, only their costs and GHG emissions so the scenarios have the same sequences as the base case. The impacts of different objectives and sequencing approaches on the optimal sequences of alternative water supply sequences and on objective function values are discussed in Sections 2.5.1 and 2.5.2, respectively.

Table 2.7 Staging of water supply options for the optimal sequence plans obtained from the analyses conducted

Water supply options	Decision stage at which to implement water supply options, P_c (c = 1 to 8)																							
	BU method												BTT method											
	w_1=1; w_2=0				w_1=0; w_2=1				w_1=0.5; w_2=0.5				w_1=1; w_2=0				w_1=0; w_2=1				w_1=0.5; w_2=0.5			
	Base case scenario	Increased River Murray supply scenario	Low population growth scenario	High population growth scenario	Base case scenario	Increased River Murray supply scenario	Low population growth scenario	High population growth scenario	Base case scenario	Increased River Murray supply scenario	Low population growth scenario	High population growth scenario	Base case scenario	Increased River Murray supply scenario	Low population growth scenario	High population growth scenario	Base case scenario	Increased River Murray supply scenario	Low population growth scenario	High population growth scenario	Base case scenario	Increased River Murray supply scenario	Low population growth scenario	High population growth scenario
50GL desalination plant	1			1	2			1	3			1	1				2			1	1			
100GL desalination plant																1								1
50GL desalination plant expansion				3				5				5								5				
Brownhill-Keswick stormwater harvesting scheme	3	4	1	1	1		1	1	1		1	1	1	1	1	5	1		1	1			1	4
Sturt River stormwater harvesting scheme	7			2	1		1	1	1		1	1	3	4	1		1		1	4			1	
Field River stormwater harvesting scheme	2	3	1					3	2				7		1							7		
Pedler Creek stormwater harvesting scheme	1	1	1	1	1	6	1	1	1	1	1	1				4	1	1	1	1	1		1	4
1kL rainwater tank				8		1	1	3		3		3						1	1				1	
2kL rainwater tank					1				1		1				1						2	1		
5kL rainwater tank			1													6								6
10kL rainwater tank																	1			1				

Table 2.8 Optimal value of costs and GHG emissions for the sequence plans

	BU method		BTT method	
	PV of cost ($ million)	*PV of GHG emissions ($MtCO_2$-e)*	*PV of cost ($ million)*	*PV of GHG emissions ($MtCO_2$-e)*
Base case scenario (S1)				
Sequence plans for w_1=1; w_2=0	5,644	18.60	5,636	18.24
Sequence plans for w_1=0; w_2=1	6,176	12.88	6,561	12.89
Sequence plans for w_1=0.5; w_2=0.5	6,025	13.33	5,812	16.64
Increased River Murray supply scenario (S2)				
Sequence plans for w_1=1; w_2=0	2,960	15.28	2,959	15.03
Sequence plans for w_1=0; w_2=1	3,541	14.44	3,636	13.59
Sequence plans for w_1=0.5; w_2=0.5	3,399	14.50	3,383	14.50
Low population growth scenario (S3)				
Sequence plans for w_1=1; w_2=0	3,746	10.20	3,717	10.03
Sequence plans for w_1=0; w_2=1	4,204	8.83	4,198	8.80
Sequence plans for w_1=0.5; w_2=0.5	3,827	9.25	3,858	9.17
High population growth scenario (S4)				
Sequence plans for w_1=1; w_2=0	7,800	23.84	7,597	25.66
Sequence plans for w_1=0; w_2=1	8,133	21.96	8,448	20.85
Sequence plans for w_1=0.5; w_2=0.5	8,103	21.96	8,048	25.62
Low discount rate scenario (S5)				
Sequence plans for w_1=1; w_2=0	6,983	24.41	6,959	24.00
Sequence plans for w_1=0; w_2=1	7,627	17.00	8,055	16.81
Sequence plans for w_1=0.5; w_2=0.5	7,536	17.47	7,099	21.75
High discount rate scenario (S6)				
Sequence plans for w_1=1; w_2=0	4,759	14.76	4,761	14.45
Sequence plans for w_1=0; w_2=1	5,185	10.15	5,421	10.36
Sequence plans for w_1=0.5; w_2=0.5	4,998	10.56	4,955	13.29

2.5.1 Impact of Different Objective Function Weightings and Sequencing Approaches On Optimal Sequences of Alternative Water Supply Sources

The results in Table 2.7 indicate that the objective function weightings do not have a significant impact on the optimal sequences of the alternative water supply sources. In general, stormwater and rainwater sources are used in preference to desalination when the additional demand is relatively small, as is the case in the River Murray Supply (S2) and Low Population Growth (S3) scenarios. In the case of scenario S2, this is because a larger amount of water is available at the beginning of the planning horizon, as there is restriction on the availability of the supply from the River Murray, as is the case for the other scenarios. Consequently, the additional demand that needs to be supplied by the alternative water supply sources over the planning horizon is relatively small, as is the additional capacity required at the first time step. In the case of scenario S3, overall demand is low because there is a negative population growth rate, so that the highest demand occurs at the beginning of the planning horizon. However, as the availability of the existing supply from the River Murray is restricted in this scenario, there is a need to provide additional capacity at the first decision stage. As a result of the relatively small requirement for additional demand, the optimal sequence plans for the above scenarios only include stormwater and rainwater sources. For scenario S3, all additional sources are included at the first time step to cover for the large initial shortfall. As discussed above, there is no need to include additional sources at subsequent decision points, as demand is decreasing. For scenario S2, the additional supply options are added at various stages of the planning horizon, as the initial shortfall is smaller, as discussed above, and demand increases over the planning horizon as a result of population growth, necessitating the addition of alternative water sources throughout the planning horizon.

When additional demand is relatively high, as is the case for the Base Case (S1) and High Population Growth (S4) scenarios, desalinated water is included in the optimal sequencing plans (Table 2.7). This is partly because the capacity of the stormwater and rainwater sources is insufficient to meet demand and partly because the effective unit costs and GHG emissions of desalinated water are significantly lower for demands that are close to the desalination plant’s capacity, due to the plant’s high capital costs and GHG emissions. These high capital costs and GHG emissions, coupled with the high initial demand shortfall resulting from the reduced supply from the River Murray, are primarily responsible for the fact that the desalination plants are implemented in the early stages of the planning horizon.

While the sequence plans obtained for different objective function weightings follow the general trends outlined above, there are some differences. For example, when optimising for cost (i.e. w_1=1; w_2=0), stormwater harvesting schemes are generally selected first, as they have a lower NPV of cost over the planning horizon than rain- and desalinated- water sources (Table 2.7). However, when optimising for GHG emissions (i.e. w_1=0; w_2=1), rainwater tanks are the preferred choice, followed by the stormwater harvesting schemes. The results in Table 2.7 also show that the use of desalinated water is less attractive from a GHG emission perspective than from a cost-perspective, as evidenced by the fact that the desalination plants are generally implemented earlier in the planning horizon when optimising for cost than when optimising for GHG emissions. Interestingly, if the available supply exceeds demand after the addition of rainwater and stormwater sources at a particular decision point, this additional supply is used to substitute for the existing supply from the River Murray. This is because the GHG emissions per unit supply from the River Murray are higher than those for the rainwater and stormwater sources due to the need to pump water from the River Murray to the Onkaparinga River via the Murray-Onkaparinga pipeline and on to other storage reservoirs (Figure 2.6).

The results in Table 2.7 show that there is little difference between the solutions obtained using the BU and BTT methods. This is primarily caused by the fact that in most cases, a significant amount of additional supply is required at the first decision stage for three of the four scenarios, as discussed previously. However, in general, when the BTT method is used, fewer, larger supply options are chosen, as expected, as the available options are selected so as to satisfy the demand at the end of the planning horizon and then distributed along the planning horizon in an optimal manner. In other words, when the BTT method is used, the demand that needs to be satisfied at the end of the planning horizon is considered at the first decision stage. However, this is not the case when the BU method is used, as only the demand requirements at the next decision stage are considered. The most notable example of this is when optimising for cost and both cost and GHG emissions for scenario S4, where a single 100GL desalination plant is selected at decision stage 1 when the BTT method is used, while the same total volume of desalinated water is added by using a 50GL desalination plant at stage 1 and a 50GL expansion of this plant at stages 3 or 5 when the BU method is used.

2.5.2 Impact of Different Objective Function Weightings and Sequencing Approaches On Objective Function Values

The results in Table 2.8 indicate that although the objective function weightings do not have a large impact on optimal water source allocation sequences, they can have a significant impact on the costs and GHG emissions of the optimal solutions. When the BU method is used, the differences in optimal costs obtained with different objective function weightings range from 4.1% for scenario S4 to 16.4% for scenario S2. When the BTT method is used, the corresponding values are 10% and 18.6%. Optimal GHG emissions range from 5% to 44% when the BU method is used and from 10.6% to 41.6% when the BTT method is used for scenario S2 and S1, respectively.

Typical tradeoff curves between cost and GHG emissions for solutions with different objective function weightings obtained using the two different sequencing approaches are given in Figure 2.7 for scenario S1. The dollar costs associated with reducing 1 tonne of GHG emissions when moving between solutions on the tradeoff curves are also shown to provide additional insight into the nature and potential practical implications of the tradeoffs. As can be seen, the cost of reducing 1 tonne of GHG emissions in order to move from the least cost solution to the solution that gives equal weighting to the cost and GHG emission reduction objectives is $72.3 when the BU method is used. This cost increases to $335.6 per tonne of CO_2-e when moving from the solutions with equal weighting of the two objectives to the solution that minimises GHG emissions. The corresponding values for the BTT method are $110 and $119.7 per tonne of CO_2-e. Based on these costs, it is unlikely that the lower GHG emission solutions would be implemented in practice, given that the current carbon price is Australia is $23 per tonne (Australian Government, 2011b).

While the objective function weightings and optimisation method used can have a substantial impact on costs and GHG emissions, as discussed above, the impacts of the demand and discount rate scenarios can be much more significant (Table 2.8). The maximum difference in cost for the different demand scenarios is 63.5% when the BU method is used and 65% when the BTT method is used. The corresponding values for GHG emissions are 63% and 65.7%. This difference is primarily caused by the need for additional water supply sources with different capacities as a result of differing demands in the various scenarios, as discussed previously. For example, for scenario S3, the addition of three stormwater harvesting schemes and rainwater tanks of a given size are sufficient to satisfy demand. In contrast, for scenario S4, 100 GL of desalinated water is typically required in addition to the stormwater harvesting schemes and rainwater tanks.

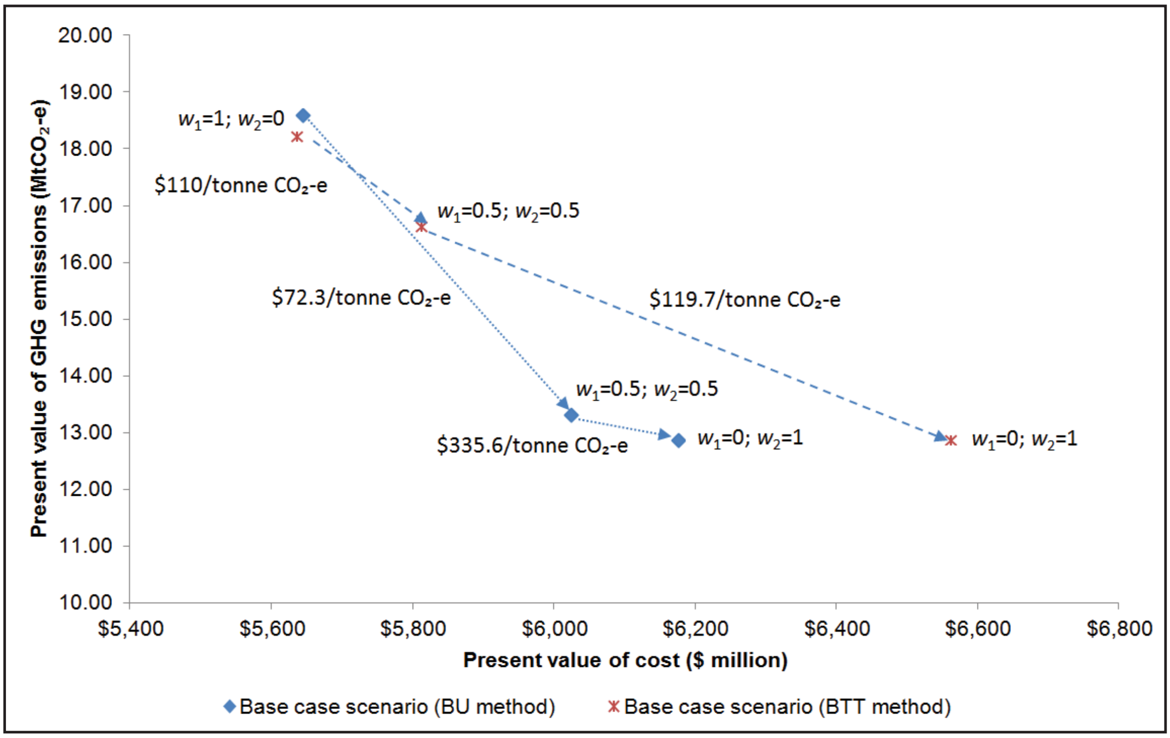

Figure 2.7 Carbon cost mapping of the optimal sequence plans of base case scenario generated using BU and BTT method

The maximum difference in cost for the different discount rate scenarios (i.e., S5 and S6) is 37.6% when the BU method is used and 65% when the BTT method is used. The corresponding values for GHG emissions are 58.4% and 56.8%. These differences in costs and GHG emissions are due to the differing effects of discount rates on capital and operating costs and GHG emissions. For low discount rates, use of the BU method results in higher total objective function values (see Table 2.8) because of the duplication of water supply options in later decision stages (see Table 2.7), which receive less discounting. In contrast, when the discount rate is high, the BU method produces sequence plans with lower costs and GHG emissions compared with those obtained using the BTT method, because the costs, especially the capital costs, are discounted at 8% and the GHG emissions are discounted at 3%. For these reasons, the capital costs or GHG emissions associated with frequent duplication or the expansion of water supply options does not impact significantly on the total objective function values of the sequence plans generated using the BU method.

As expected, the BTT method usually results in better values for the objective function that is being optimised (Table 2.8). The biggest difference in the costs obtained using the BU and BTT methods when optimising for this objective is around 2.7% and occurs for scenario S4, whereas the biggest saving in GHG emissions when optimising for this objective is around 6.3% and occurs for scenario S2. However, these modest savings come at the expense of adaptability. For example, if the BTT method were used to obtain the optimal sequence for scenario S4 when optimising for cost or an equal weighting of cost and GHG emissions, a 100GL desalination plant would be built at the first decision stage. However, if the actual demand is less than the predicted demand (e.g. scenario S1 or S3 actually occurred), there would be a large amount of excess capacity and associated capital costs and GHG emissions. In contrast, if the BU method were used in this situation, only a 50GL desalination plant would be built at the beginning of the planning horizon, with a 50GL expansion scheduled at a later date. However, at the time of the scheduled expansion, it would be known that the actual demand is less than the projected demand and the expansion would not be implemented.

The magnitude of the discount rate also has an effect on the relative merits of the two sequencing approaches. Based on the results for the case study (Table 2.8), it is better to choose the water supply options that meet the demand for the next decision stage, and then expand or duplicate these as required if the discount rate is high, thus favouring the BU method. In contrast, if the discount rate is low, it is better to deploy the water supply options with larger capacities initially, as is the case when the BTT method is used.

2.5.3 Implications for Decision Making

The purpose of the proposed approaches is to identify the sequence plans that provide the optimal trade-offs between objectives under a set of assumed conditions. As all identified sequence plans are Pareto optimal, other techniques, such as multi-criteria decision-analysis, are required in order to choose between solutions, as the ranking of Pareto optimal solutions requires value judgements on the relative importance of the different objectives. As discussed previously, from a cost perspective, stormwater harvesting is preferred to rainwater tanks, while the reverse applies if reduction in GHG emissions is the primary objective. In addition, desalination is more desirable from a cost, rather than from a GHG emission perspective. However, whether cost or GHG emission reduction is more important is based on a value judgement.

Whether solutions obtained using the BU or BTT methods are preferable depends on the degree of confidence in the assumed design conditions. If the design conditions are known with relative certainty, implementation of the solutions obtained using the BTT would be preferable, as they result in better objective function values for the assumed conditions. However, the solutions obtained using the BU method are likely to be preferable if future conditions are uncertain, as this allows for more flexibility over the planning horizon. If there is considerable uncertainty in the objective function values, multi-criteria decision-analysis approaches that cater to this uncertainty can be used in order to rank sequence plans on the Pareto front (e.g. see Hyde and Maier, 2006).

2.6 Conclusions and Recommendations

The two sequencing approaches – the BU and BTT methods – evaluated in this paper incorporate multiple objectives into the sequencing of water supply projects at the regional scale. The approaches consider various water supply options, such as traditional surface water resources and desalination, as well as stormwater and rainwater harvesting. The approaches are tested using a case study based on the southern Adelaide WSS over a planning horizon of 40 years, with sequence plans optimised for cost and GHG emissions under a range of demand and discount rate scenarios. The resulting sequence plans include a mixture of stormwater harvesting schemes, rainwater tanks and desalinated water, depending on the scenario. The selection of stormwater harvesting schemes is preferred from a cost minimisation perspective, whereas rainwater tanks and the stormwater harvesting schemes are best from a GHG minimisation perspective. While these sources of water are sufficient for the lower demand scenarios (S2 and S3), the addition of 50 or 100 GL of desalinated water is required for the higher demand scenarios (S1 and S4).

When the BU method is used, each decision stage is optimised in sequential order. Consequently, the BU method is flexible and responsive to future changes, such as demand reduction. However, it generally results in less favourable objective function values compared with those obtained using the BTT method for the selected design conditions, assuming that these design conditions actually occur. When using the BTT method, the optimal combination of water supply options is identified for the final decision stage. Thereafter, selected water supply options are scheduled at each decision stage, starting with the initial planning stage and working forwards in time. The BTT method therefore poses a simpler optimisation problem at each decision stage since the available water supply options are restricted. It generally also results in more favourable objective function values compared with the BU method for the selected design conditions. However, it is less able to adapt to changed conditions during the planning horizon.

The results for the case study based on the southern Adelaide WSS show that optimal sequence plans obtained using the BTT method include the implementation of water supply options with large capacities (i.e., 50GL desalination and 10kL rainwater tanks) first, leaving fewer expansion choices later. In contrast, the sequence plans obtained using the BU method include only those supply options required to satisfy demands for the next staging interval. Thus, if the actual demands are higher than the initial demand projections over the planning horizon, sequence plans generated using both the BU and BTT method may not be practicable, however, the BTT method is likely to result in sequences with lower costs and GHG emissions than the BU method, which tends to use smaller component sizes during the earlier stages of the planning horizon, with more expansion of components in the later planning stages.

However, should the actual demands over the planning horizon be less than the initial demand projections, the BTT method would be unlikely to perform as well as the BU method. The use of large capacity water sources in the initial stages which would not be needed if actual demands are lower than the projected demands would result in higher costs and greenhouse gas emissions. In contrast, when the BU method is used, only the water supply options (i.e. stormwater harvesting schemes and 2kL rainwater tanks) that are required to satisfy the demands for the next staging interval are implemented. Consequently, the water supply options selected at the early decision stages will only be slightly oversized, and later expansion options would not need to be implemented, resulting in lower costs and GHG emissions overall.

Additionally, for low to moderate discount rates (i.e., 4-6% for economic; 0% for GHG emissions), the BTT method produced sequence plans with better objective function values (i.e., lower cost and GHG emissions) by initially selecting the water supply options with larger capacity. Conversely, the BU method is efficient in generating sequence plans with lower objective function values for higher discount rates (i.e., >8% for economic; >1.4% for GHG emissions) by selecting the water supply options that meet the demands for the next decision stage, and then expanding or duplicating these as required.

The results also showed that significant tradeoffs exist between the NPV of costs and GHG emissions for the optimal sequence plans obtained using different objective function weightings. However, the extent of this tradeoff is affected significantly by the demand and discount rate scenarios. The Base Case solution obtained using the BU method for equal objective function weighting appears to provide a good compromise solution, with an expected total present value of cost of $6,025 million and present value of GHG emissions of 13.33MtCO_2-e (with an economic discount rate of 6% and GHG emissions discount rate of 1.4%). As part of this solution, household rainwater tanks and various stormwater harvesting schemes will be required by 2015 and a 50GL desalination plant by 2020. However, even though use of the BU method affords some flexibility, as discussed above, in light of the significant impact of uncertainties surrounding demand and discount rates, the explicit consideration of this uncertainty as part of the optimal sequencing process (Beh et al., 2011, Dorini et al., 2011) should be considered in future studies.

While the proposed methods are able to produce optimal sequences of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives, they have a number of limitations that should be addressed in future work, as outlined below.

- As single-objective optimisation LP is used in this study, the weighting method has to be used to cater for multiple objectives, requiring individual optimisation runs to be repeated with different combinations of weightings in order to obtain various solutions on the Pareto front. In addition, due to the discrete nature of different combinations of objective function weightings, these approaches may fail to identify optimal solutions in non-convex regions of the Pareto front. This limitation can be overcome by using multi-objective optimisation algorithms, such as multi-objective evolutionary algorithms (e.g. Kasprzyk et al., 2013a), in future studies.
- When the BU and BTT approaches are used, simplified formulations of the optimisation problem are used, which are computationally efficient, but may fail to identify the globally optimal sequence plan. This shortcoming can be overcome by re-formulating the optimisation problem so that the whole solution space is explored. This can be achieved by linking an evolutionary algorithm with a simulation model of the potential water supply sequences, although this would reduce computational efficiency significantly.

- The calculated reliability of the overall system is only an approximation, as it is based on the individual reliabilities of the various sources, which ignores potential interactions between sources. This limitation could be addressed by adopting a combined simulation – optimisation approach.
- Reliability is considered as a constraint to be satisfied at each decision stage. However, there might be advantages in including reliability as an objective, as this enables trade-offs between reliability and other objectives to be explored explicitly. In addition, the use of other risk-based system performance measures that not only take account of the probability of failure (i.e. demand exceeding supply), but also the consequences of system failure (e.g. Hall et al., 2012, Yazdani et al., 2011), are of consideration.
- Only supply expansion options are currently considered. It would be beneficial to also include demand management options as decision variables in future studies.

2.7 Acknowledgements

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2.8 Supplementary Material

2.8.1 Calculation of Yield For Potential Water Supply Options

For stormwater harvesting schemes, the yield is dependent on the total impervious and pervious areas of catchments, wetland capacity, injection rate and discharge rate for the wetlands and aquifers. Thus, these factors are important for the simulation model in order to generate the yields for each scheme.

For impervious catchments, runoff volume is calculated by multiplying the effective area, which is the total connected impervious area, by the runoff depth. The effective areas of roofs and pavements (Table 2.9) are based on the data given in Wallbridge and Gilbert (2009). The daily runoff depth is determined by:

$$RO = (R - IL) \times OF \tag{2.20}$$

where RO is the daily runoff ($RO \geq 0$); R is the daily rainfall; IL is the initial loss; and OF is the ongoing fraction of runoff. Initial losses of 1mm for roof runoff and 2mm for pavement runoff are assumed, while ongoing fractions of 0.9 and 0.85 are assumed for roofs and pavements, respectively (Wallbridge and Gilbert, 2009).

Table 2.9 Effective impervious area properties for the stormwater catchments

Stormwater catchment	Effective roof area (km^2)	Effective pavement area (km^2)
Brownhill-Keswick	16.95	16.84
Sturt Creek	9.59	11.51
Field River	4.62	4.46
Christie Creek	3.47	3.82
Onkaparinga River	4.41	4.85
Pedler Creek	1.77	3.01

For pervious catchments, the rainfall runoff model embedded in *WaterCress* (Clark et al., 2002) required calibration and validation in order to accurately simulate runoff. Thus, rainfall runoff models for the stormwater harvesting schemes are developed for the six catchments given in Table 2.10, which range in area from 37.8km^2 to 128.4km^2. For the case study, the WC1 rainfall runoff model is selected to determine runoff from pervious catchments following its successful use by Wallbridge and Gilbert (2009) for this purpose. For further details of the WC1 model, the reader is referred to the *WaterCress* user manual, available from www.waterselect.com.au.

Table 2.10 Catchment area, periods of calibration and validation and Nash Sutcliffe coefficient for models of pervious catchments for the stormwater harvesting schemes

Stormwater Catchment	Catchment Area (km²)	Calibration Period	Validation Period	Nash-Sutcliffe coefficient (NS)	
				Calibration	Validation
Brownhill-Keswick Creek	67.9	26/01/1996 – 24/01/2008	25/01/2008 – 25/01/2012	0.86	0.83
Sturt Creek	128.4	01/02/2008 – 03/02/2011	04/02/2011 – 02/02/2012	0.81	0.74
Field River	55.3	16/04/2010 – 16/06/2011	17/06/2011 – 02/02/2012	0.80	0.53
Christie Creek	37.8	01/02/2001 – 28/01/2009	29/01/2009 – 01/02/2012	0.81	0.55
Onkaparinga River	112.9	01/01/2007 – 03/01/2010	04/01/2010 – 01/01/2012	0.97	0.84
Pedler Creek	106.2	01/08/2000 – 28/07/2008	29/07/2008 – 01/08/2011	0.91	0.91

It should be noted that the WC1 model requires rainfall and evaporation inputs to calculate runoff. Daily rainfall data and monthly evaporation data from five rainfall stations were obtained from the Patched Point Dataset (PPD) (Jeffrey et al., 2001), while flow data from six gauging stations, which are used for model calibration and validation, are sourced from the South Australian Government Department of Environment, Water and Natural Resources' Surface Water Archive (https://www.waterconnect.sa.gov.au/SWA). Approximately 60-70% of available data are used for calibration, while the remaining data are used for validation, as given in Table 2.10. The rainfall runoff models are calibrated using a genetic algorithm (GA). Initial GA parameter trials examined populations of 100 to 400, generations of 100 to 400 and values of 0.6-0.9 for the probability of crossover, with final GA parameter selection being 400 for population, 350 for maximum number of generations, 0.7 for probability of crossover and 0.1 for the probability of mutation. Time series and scatter plots of actual and predicted values are used to provide a visual assessment of the performance of the developed models. In addition, the Nash Sutcliffe (NS) coefficient is used as an analytical performance measure, as it is commonly used for this purpose and indicates how well the model explains the variance in the observations relative to that of the mean (Bennett et al., 2013). The natural logarithmic-transformed weekly flow is used to calculate the NS coefficient as the objective function for calibration due to the extremely positively-skewed nature of the stormwater schemes' runoff. The calibration is repeated from 10 different random starting positions in the parameter space to ensure near-globally optimal parameter values are obtained.

It is necessary to determine whether the RRO models produce results within the range of accuracy required for the case study. The catchment parameterizations are judged adequate if the value of NS for the validation set is greater than 0.5, which is the case for all catchments (Table 2.10).

Hydrological conditions (e.g., rainfall and evaporation) are needed as inputs to the simulation model used to estimate the yield of the selected water supply system at each decision stage. For the case study, the variability of rainfall is taken into account. Thus, Stochastic Climate Library (SCL) (www.toolkit.net.au/scl) is used to generate 1000 sets of stochastic rainfall series 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 studies (Srikanthan, 2005a). 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.

2.8.2 Costs

Costs for water supplied by the reservoirs are determined from the costs of the associated water treatment plant (WTP) facilities. As both the Myponga and the Happy Valley WTPs are existing facilities in the southern Adelaide water supply system (WSS), the capital costs of these plants are not included. However, reservoir operating costs are included, including the costs of power and chemicals used in water treatment and the cost of labour for the operation of the WTPs. Like the reservoirs, the River Murray is a current water supply source in the southern Adelaide WSS. Therefore, only operating costs are calculated for this source. The operating costs for the River Murray relate only to electricity usage associated with powering the pumps to transfer water from the River Murray to the Onkaparinga River. It should be noted that although the reservoirs and the River Murray are not included in the development of the optimal sequence plans, as they are existing water supply sources, their operational costs are included in order to enable the total costs of meeting the required demand to be calculated. The estimated unit operating costs for the reservoirs and River Murray are given in Table 2.11.

The capital cost of a desalination plant with an annual capacity of 100GL is \$1.83billion, whereas the cost for a 50GL plant is \$1.347billion (Government of South Australia, 2009a). For this case study, the desalination plant's operating costs are considered to be for electricity and ongoing costs, such as maintenance. The energy required to treat 50GL of water per year is estimated to be 250GWh, and the energy required for the delivery pipeline of the 50GL plant is 35GWh (Government of South Australia, 2009a, SA Water, 2009). Assuming that energy and other ongoing resource inputs for the 100GL plant are twice those for the 50GL plant, a total of 570GWh of electricity is required annually for the 100GL plant (Government of South Australia, 2009a). The calculated unit capital and operating costs for the desalination plants of different capacities are given in Table 2.11.

For the stormwater harvesting schemes, the capital cost of each scheme is obtained from the Urban Stormwater Report (Wallbridge & Gilbert, 2009). However, these capital costs do not include land acquisition and distribution costs. Distribution costs and operating costs for this case study are therefore estimated from three aquifer storage and recovery (ASR) schemes in Adelaide for which distribution costs are available. The estimated operating cost for each stormwater harvesting scheme incorporated the cost of labour, operation and maintenance of mechanical, electronic and control equipment, replacement, electricity consumption, landscaping, wetland plant maintenance, UV treatment, monitoring and licensing fees. The calculated unit capital and operating costs for the different stormwater harvesting schemes are given in Table 2.11.

The calculated unit capital and operating costs for the rainwater tanks of different sizes are provided in Table 2.11. For household rainwater tanks, the capital costs include the purchase cost of the tank and pump, as well as costs associated with tank delivery and installation and plumbing the tank into the household water system. There are also some operating costs associated with the energy required for pumping and maintenance. Estimation of the operating cost is based on (i) $0.05/kL for ongoing operating and maintenance; (ii) $20 per year of additional maintenance (Tam et al., 2010).

Table 2.11 Capital and operating cost for the various water supply options

Water supply options	Capital cost ($)	Unit operating cost ($/kL)
Happy Valley reservoir	-	0.03
Myponga reservoir	-	0.23
River Murray	-	0.44
50GL desalination plant	1,347,000,000	1.00
100GL desalination plant	1,830,000,000	1.00
50GL desalination expansion	483,000,000	1.00
Stormwater harvesting schemes :		
Brownhill & Keswick Creek	160,025,000	1.23
Sturt River	194,193,000	1.23
Field River	35,689,000	1.23
Pedler Creek	110,682,000	1.23
Household rainwater tanks:		
1kL	2,181	0.78
2kL	2,464	0.68
5kL	3,024	0.64
10kL	3,560	0.63

2.8.3 GHG Emissions

The capital values of GHG emissions for the existing water sources (i.e., reservoirs and the River Murray) in the southern Adelaide WSS are not included. However, the operational GHG emissions of the reservoirs and River Murray are included in order to enable the total GHG emissions of meeting the required demand to be calculated. The operating GHG emissions for the Happy Valley and Myponga WTPs are estimated from the total GHG emissions from the Adelaide metropolitan water treatment plants and networks in 2010, which amounted to 25,813 tonnes (SA Water, 2011). There are six water treatment plants in the metropolitan area, so the GHG emissions associated with their operation are estimated according to their capacities. The estimated unit operating GHG emissions for the reservoirs and River Murray are given in Table 2.12.

The capital GHG emissions for the desalination plant can be attributed to (i) the construction materials for the main plant, delivery pipeline and power facilities onsite; (ii) the electricity and diesel required for construction; and (iii) vegetation clearance. As it is assumed that the plant is designed to be able to increase its capacity from 50 to 100GL/year, there would be minimal additional construction energy required to accommodate this expansion (Government of South Australia, 2009a). Therefore, an indicative 10% of capital GHG emissions is added for the 100GL plant to account for any additional buildings or processing equipment (Table 2.12).

The desalination plant operating GHG emissions are based on GHG emissions associated with the electricity required for treatment and the delivery pipeline, chemicals, membranes and diesel. These are converted to GHG emissions using the electricity GHG emission factor of 0.81kgCO_2-e/kWh, while GHG emissions for chemicals, membranes and diesel for the 50GL plant are 260,000 tonnes (Government of South Australia, 2009a), which are doubled for the 100GL plant. The estimated capital and unit operating GHG emissions for the desalination plants of different capacities are given in Table 2.12.

Table 2.12 Capital and operating GHG emissions for the various water supply options

Water supply options	Capital GHG emissions (kgCO_2-e)	Unit GHG emissions (kgCO_2-e/kL)
Happy Valley reservoir	-	0.24
Myponga reservoir	-	0.22
River Murray	-	2.93
50GL desalination plant	228,538,259	5.41
100GL desalination plant	237,103,259	5.43
50GL desalination expansion	8,565,000	5.41
Stormwater harvesting schemes :		
Brownhill & Keswick Creek	7,248,734	2.04
Sturt River	7,350,767	2.06
Field River	3,576,467	6.05
Pedler Creek	5,643,330	1.60
Household rainwater tanks:		
1kL	718	1.22
2kL	1,251	1.22
5kL	2,897	1.22
10kL	4,635	1.22

The capital GHG emissions for the stormwater harvesting schemes are estimated based on the embodied energy from the amount of concrete and energy required to construct the wetlands and aquifer storage and recovery wells (Treloar, 2000). For the case study, it is assumed that the water is gravity fed into the aquifers and hence the operating GHG emissions consisted of only the pump power associated with the extraction of the water from the aquifers to supply the demand. The static head for the ASR wells depends on the type of aquifer and the available storage head of the aquifer, thus a static head of 150m (Spies and Dandy, 2012) is assumed for the case study. The calculated capital and unit operating GHG emissions for the different stormwater harvesting schemes are given in Table 2.12, along with the calculated capital and unit operating GHG emissions for rainwater tanks of different sizes.

The majority of GHG emissions associated with rainwater tanks result from the energy used in their construction. The capital GHG emissions for different sizes of HDPE rainwater tanks are estimated using the mass of the tanks (30kg for 1kL tank, 54kg for 2kL tank, 125kg for 5kL tank and 200kg for 10kL tank) (AAA Poly Tanks, 2011). The embodied energy of HDPE is 103MJ/kg and a GHG conversion factor of 0.98kgCO_2-e/GJ can be assumed (Centre for Building Performance Research, 2007). Recent monitoring of rainwater tanks suggests that energy consumption is 1.5 kWh per kL of rainwater used, given the most common pump and rain switch system (Retamal et al., 2009). For households using rainwater for toilet flushing, laundry and outdoor use, a range of 0.9 to 2.3 kWh per kL is considered (Retamal et al., 2009). Therefore, energy consumption of 1.5kWh per kL of rainwater reuse is used in the case study in order to estimate operating GHG emissions.

Chapter 3

3 Scenario Driven Optimal Sequencing under Deep Uncertainty – Paper 2

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Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

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Contribution to the Paper	Conceptualisation and development of approach, modelling, analysis of results, preparation of manuscript.		
Signature		Date	1/4/2015

Name of Co-Author	Holger Maier		
Contribution to the Paper	Research supervision and review of manuscript.		
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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.

3.1 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 (Kang and Lansey, 2014, Beh et al., 2014, Mortazavi-Naeini et al., 2014, Ray et al., 2012), the scheduling of pumps and rehabilitation activities in water distribution systems (Kleiner et al., 1998, Savić et al., 2011, Zheng and Zecchin, 2014, Dandy and Engelhardt, 2001), 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, Zhang and Barten, 2009, Simon and Etienne, 2010), the scheduling of irrigation water (Merot and Bergez, 2010, Ge et al., 2013), the scheduling of crop management activities (Lautenbach et al., 2013, Ripoche et al., 2011), the scheduling of environmental flows in rivers (Szemis et al., 2012, Szemis et al., 2013) and determining the optimal schedule of investments of conservation funding (Wilson et al., 2006, Bode et al., 2008).

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 (Gober, 2013, Dessai et al., 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, Wilson et al., 2006, Srinivasa Prasad et al., 2013). 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 3.2, 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 3.3. The results are presented in Section 3.4, before a summary and conclusions are given in Section 3.5.

3.2 Proposed Approach

As illustrated in Figure 3.1, 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).

3.2.1 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 3.1, 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 3.1), 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.

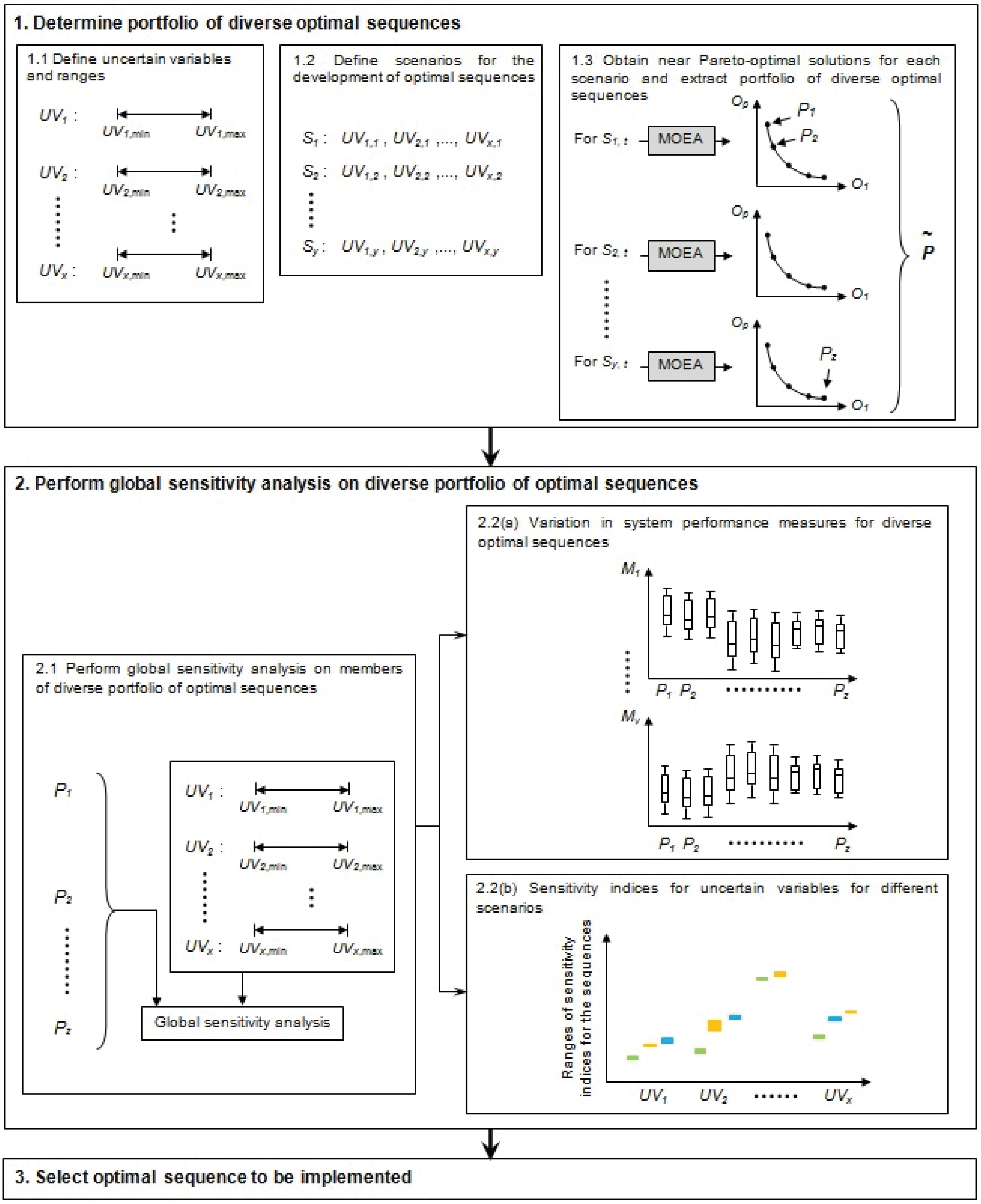

Figure 3.1 Schematic of proposed scenario driven optimal sequencing of environmental and water resource activities under deep uncertainty

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 3.1). 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 (Kasprzyk et al., 2012, Paton et al., 2013, Paton et al., 2014a, 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 3.1), which is similar to the approach used by Kasprzyk et al. (2013b) 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 (Cohon 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. Lempert and Groves, 2010, Kasprzyk et al., 2013b), to assist with this process.

3.2.2 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 3.1) 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 3.1); 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 3.1). 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 3.1) and sensitivity indices (Step 2.2(b), Figure 3.1) would be averaged over the sensitivity analyses for each of the stochastic series.

3.2.3 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 of solutions that warrant 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 3.1) (see Cui and Kuczera, 2010).
- The relative contribution of the uncertain variables to variability in performance (Step 2.2(b), Figure 3.1) 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).

3.3 Case Study

3.3.1 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. Sahin et al., 2014, Matrosov et al., 2013b, Lempert and Groves, 2010, Maier et al., 2013, Matrosov et al., 2013a, Sahin et al., Korteling et al., 2013, Paton et al., 2014a, Kang and Lansey, 2013), only some studies have considered the use of formal optimisation approaches (e.g. Kasprzyk et al., 2009, Kasprzyk et al., 2013b, Kasprzyk et al., 2012, Wang and Huang, 2014, Zeff et al., 2014, Paton et al., 2014b) 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 3.2) 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, 2009b), 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 3.2) 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 (Paton et al., 2013, Beh et al., 2014, Paton et al., 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, Paton et al., 2014b), as well as the optimal sequencing of these options without the consideration of uncertainty (Beh et 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.

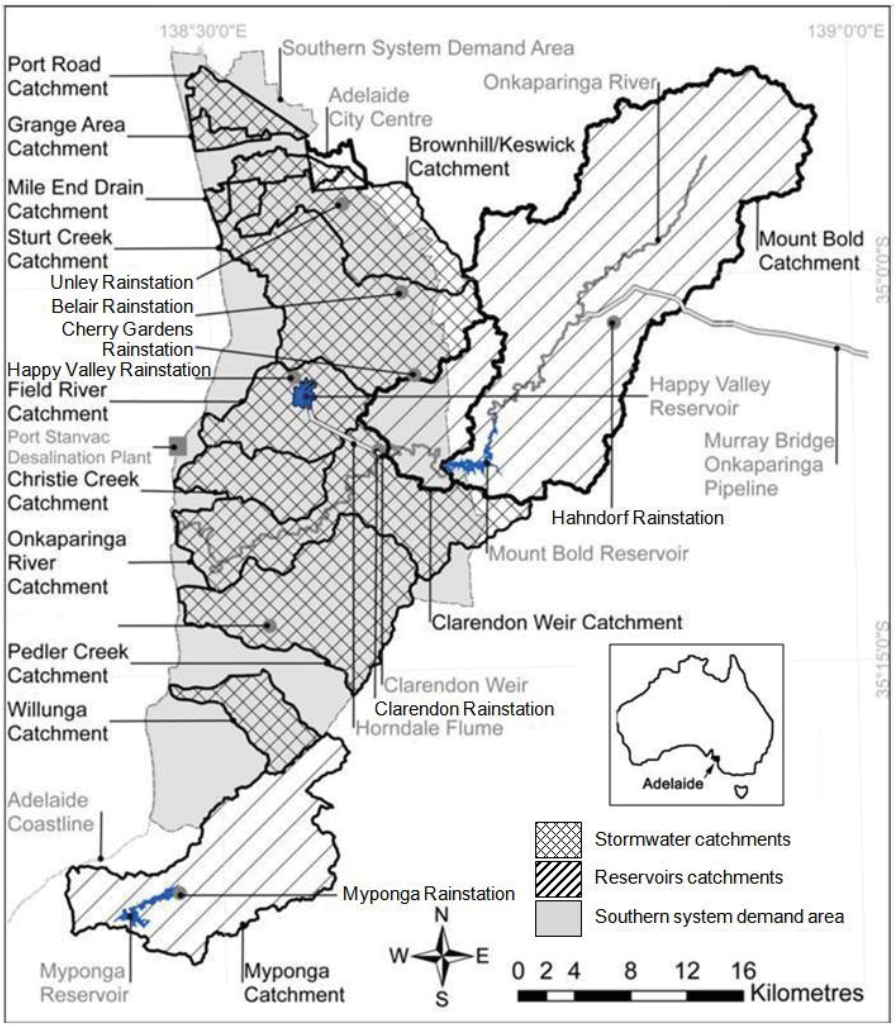

Figure 3.2 Map of the Southern Adelaide water supply system (WSS) and potential augmentation options in 2010.

3.3.2 Problem formulation

3.3.2.1 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., 2010a, 2010b, 2013), there will not be a single optimal solution, but fronts of Pareto-optimal solutions, as discussed in Section 3.2.1. The discount rates used for the calculation of the PV of cost and GHG emissions are considered to be uncertain variables (see Section 3.3.3.1). The primary constraint is that supply capacity is greater than or equal to demand at all times.

3.3.2.2 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 3.1 (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 3.1 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 3.3.2.3.

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 3.1 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 3.1 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.

3.3.2.3 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 3.3.3.1. 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 3.2). However, these were adjusted for climate change and are thus considered as uncertain variables (see Section 3.3.3.1). Further details of the *WaterCress* model are given in Beh et al. (2014) and Paton et al. (2014b).

3.3.3 Determination of Portfolio of Diverse Optimal Sequences

3.3.3.1 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 3.2 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 3.2 Uncertain variables and corresponding options

Uncertain variables	Options		
Population	Extremely high	(see Figure 3.3)	
	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 3.3). These projections are based on various assumptions of fertility, mortality, net interstate migration and net overseas migration (Australia Bureau of Statistics, 2013).

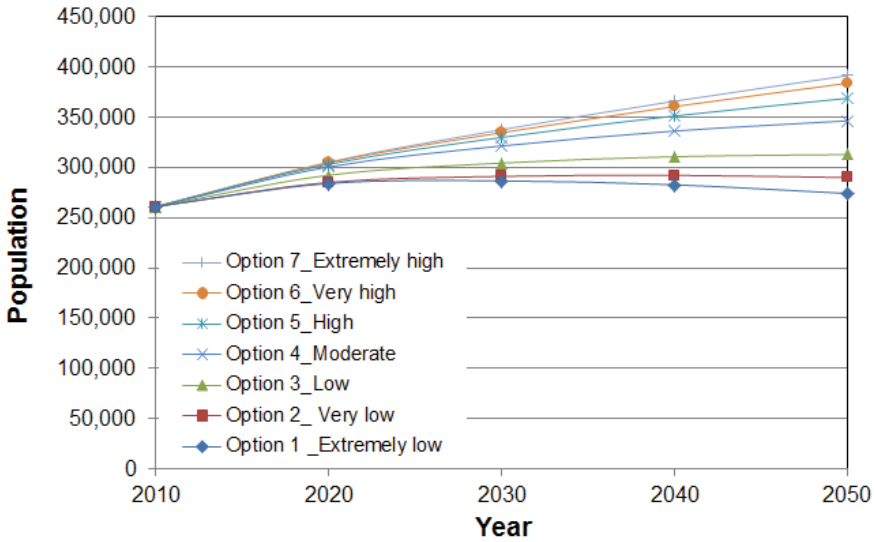

Figure 3.3 Uncertain time series of population growth consideredfor the southern Adelaide WSS to 2050 (Australia Bureau of Statistics, 2013).

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 3.2). 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) (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. (2003) 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.

3.3.3.2 Definition of scenarios

Pareto fronts of (near) optimal sequence plans are developed for seven different scenarios (see Table 3.3). 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 3.3 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

3.3.3.3 Development of Pareto fronts of diverse optimal sequences

The optimisation problem is formulated using nine decision variables, as summarised in Table 3.4. 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 3.4). 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 3.4), 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 3.3.2).

Table 3.4 Decision variables

Decision variable	Descriptions	Lower limit	Upper limit
1	50GL desalination plant implementation stage	0	5
2	100GL 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 3.4. 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., 2010b, Wu et al., 2013).

3.3.4 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 (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

$$D(y) = \sum_{i} D_i + \sum_{i<j} D_{ij} + \sum_{i<j<k} D_{ijk} + D_{12\ldots m} \tag{3.1}$$

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, $$S_i = \frac{D_i}{D} \tag{3.2}$$

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., 1982b), 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:

$$Reliability = \frac{T_s}{T} \tag{3.3}$$

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

$$Vulnerability = maximum\left(\frac{S_t}{A_t}\right) \tag{3.4}$$

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 3.2) 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, 2005b). 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).

3.3.5 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).

3.4 Results and discussion

3.4.1 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 3.4 and the selected portfolio of diverse optimal sequence plans is shown in Table 3.5.. The optimal sequences considered as potential solutions (i.e. those included in Table 3.5 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 3.5 is given below.

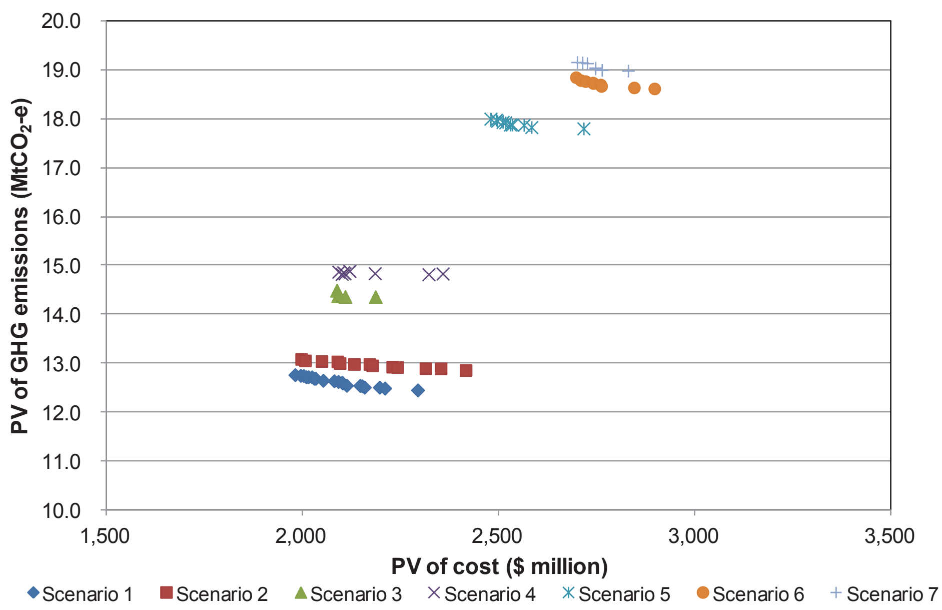

Figure 3.4 Tradeoff between PV of GHG emissions and PV of cost for the seven selected scenarios

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 3.5 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 3.5 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 3.2). Consequently, even though there is sufficient capacity 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 3.1).

3.4.2 Global Sensitivity Analysis

3.4.2.1 Sensitivity of performance of optimal sequence plans to uncertain variables

The box-and-whiskers plots in Figure 3.5 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 noticeable 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.

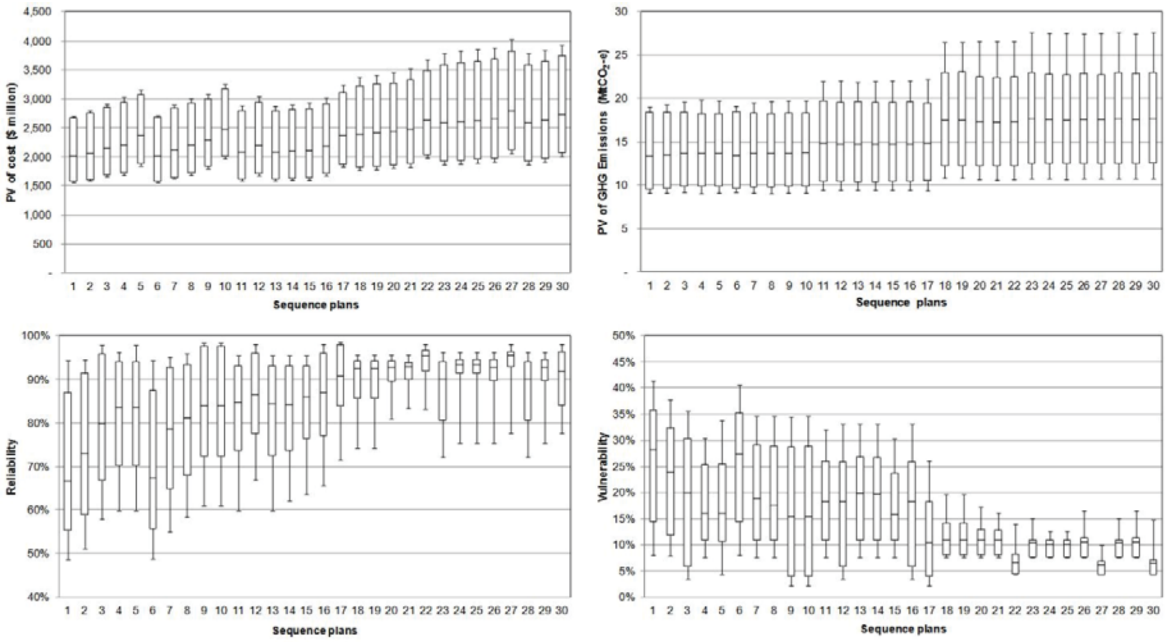

Figure 3.5 Variation in average performance values (over the 20 stochastic rainfall sequences) of the selected optimal sequence plans over the combinations of uncertain conditions considered as part of the sensitivity analysis. It should be noted that vulnerability is not zero for optimal sequences developed for the most extreme scenario due to effects of climate variability.

3.4.2.2 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 3.5) are given Figure 3.6. 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.

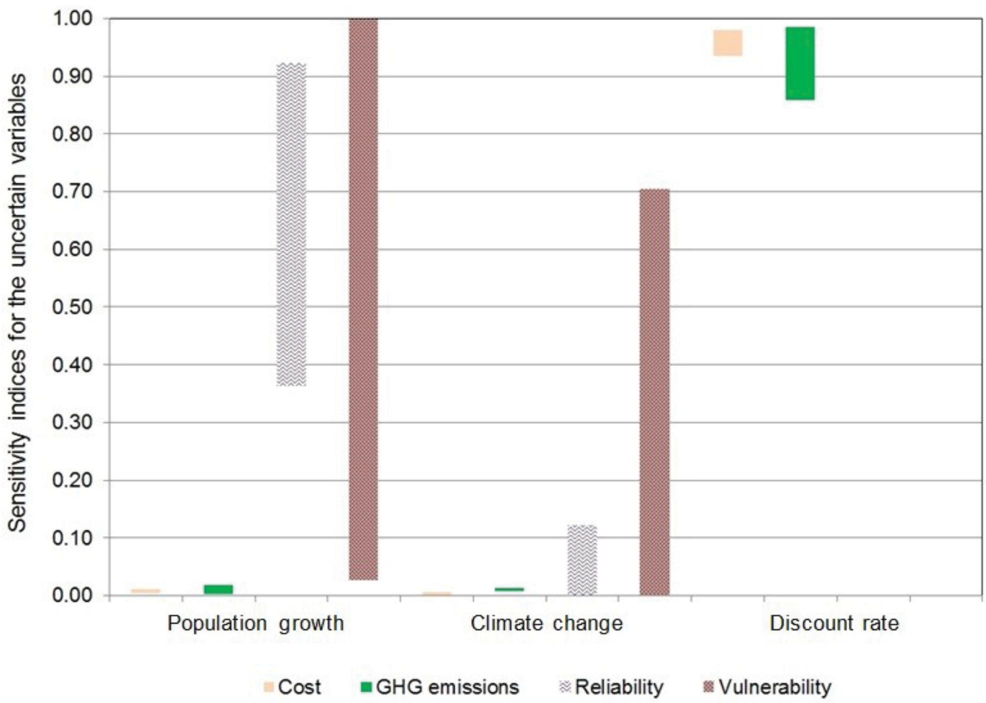

Figure 3.6 Ranges of Sobol's first order sensitivity indices for cost, GHG emissions, reliability and vulnerability over the combinations of uncertain conditions for the selected optimal sequence plans

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 3.6). 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.

3.4.3 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 3.3.5. 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 3.6) 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 3.5, 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.

3.5 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 et 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 (Sequence Plan 17) 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. Lempert and Groves, 2010, Kasprzyk et al., 2013b) and multi-criteria decision analysis (Korteling et al., 2013, Hyde and Maier, 2006), 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). 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).

3.6 Acknowledgements

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Chapter 4

4 Adaptive, Multi-Objective Optimal Sequencing Approach for Urban Water Supply Augmentation under Deep Uncertainty – Paper 3

Statement of Authorship

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Author Contributions

By signing the Statement of Authorship, each author certifies that their stated contribution to the publication is accurate and that permission is granted for the publication to be included in the candidate's thesis.

Name of Principal Author (Candidate)	Eva Beh		
Contribution to the Paper	Conceptualisation and development of approach, modelling, analysis of results, preparation of manuscript.		
Signature		Date	1/4/2015

Name of Co-Author	Holger Maier		
Contribution to the Paper	Research supervision and review of manuscript.		
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Contribution to the Paper	Research supervision and review of manuscript.		
Signature		Date	1/4/2015

Abstract

Optimal long-term sequencing and scheduling play an important role in many water resources problems. The optimal sequencing of urban water supply augmentation options is one example of this. In this paper, an adaptive, multi-objective optimal sequencing approach for urban water supply augmentation under deep uncertainty is introduced. As part of the approach, optimal long-term sequence plans are updated at regular intervals and trade-offs between the robustness and flexibility of the solutions that have to be fixed at the current time and objectives over the entire planning horizon are considered when selecting the most appropriate course of action. The approach is demonstrated for the sequencing of urban water supply augmentation options for the southern Adelaide water supply system for two assumed future realities. The results demonstrate the utility of the proposed approach, as it is able to identify optimal sequences that perform better than those obtained using static approaches.

4.1 Introduction

Formal optimization methods for sequencing or scheduling play an important role in *long-term* management and planning for a number of water resources problems, such as the sequencing of urban water supply augmentation options (Ray et al., 2012, Kang and Lansey, 2014, Beh et al., 2014, Mortazavi-Naeini et al., 2014), the sequencing of urban water supply infrastructure (Kang and Lansey, 2014), scheduling the replacement of urban water supply mains (Dandy and Engelhardt, 2001, Dandy and Engelhardt, 2006), investment scheduling for irrigated agricultural expansion planning (Allam and Marks, 1984), management of water supply systems (Housh et al., 2013) and the scheduling of environmental flows in rivers (Szemis et al., 2012, Szemis et al., 2013). The focus of this paper is on urban water supply augmentation, for which the optimal sequencing of supply sources has long been used to identify systems that maintain water supply security and minimize water supply costs (Morin and Esogbue, 1971, Becker and Yeh, 1974, Butcher et al., 1969, Atkinson, 2002). As part of the optimal sequencing process, the best combination of supply augmentation options that is able to satisfy projected demands over a long-term planning period (e.g. 30-50 years) is identified. The optimal sequencing of these options over the planning period is also determined, in recognition of the fact that demands are likely to change over time. Consequently, decisions in relation to which augmentation options should be implemented are made at a number of decision points over the planning horizon, which are generally spaced at regular time intervals (e.g. 10 years), resulting in a number of staging intervals over the planning horizon.

In the past, optimal sequencing approaches have considered traditional sources of water, such as reservoirs and groundwater, and have attempted to minimise cost objectives (Chang et al., 2009, Connarty and Dandy, 1996). More recently, multiple objectives (e.g. Beh et al., 2012, Beh et al., 2014, Mortazavi-Naeini et al., 2014) and alternative sources of water, such as desalinated water, stormwater, rainwater and reclaimed wastewater (e.g. Beh et al., 2012, Ray et al., 2012, Downs et al., 2000, Beh et al., 2014) have been considered. However, while uncertainties about future conditions, such as population growth, per capita demand and hydrological inputs, have been considered in the determination of optimal portfolios of future urban water supply and demand management options (e.g Kasprzyk et al., 2009, Kasprzyk et al., 2012, Kasprzyk et al., 2013b, Zeff et al., 2014, Paton et al., 2014a, Kang and Lansey, 2013), they have generally not been considered in the optimal *sequencing* of these options. In other words, while these uncertainties have been considered in determining *which* sources are best suited to satisfying demand at some time in the future, they have not been considered in relation to the *timing* of the implementation of these sources over the planning horizon, which is a much more complex problem. Only Ray et al. (2012) have developed a formal optimisation approach for the sequencing of long-term urban water supply augmentation options under deep uncertainty, which is uncertainty associated with multiple possible futures for which relative probabilities are unknown (e.g. climate change, population growth (Lempert, 2003). However, it should be noted that the approaches of Housh et al. (2013) and Kang and Lansey (2014) could also be used for this purpose, even though they were developed for the optimal sequencing of urban water supply infrastructure and water supply system management options, respectively.

A potential disadvantage of the approaches of Ray et al. (2012) and Housh et al. (2013) is that they are based on what are generally referred to as traditional optimization methods (i.e. linear and stochastic programming, respectively, in this case), which have a number of shortcomings compared with evolutionary optimization approaches (see Maier et al., 2014, Mortazavi-Naeini et al., 2014). Some of these shortcomings include not being able to be linked with simulation models of the urban water supply system under consideration, thereby potentially ignoring important non-linear interactions (Matrosov et al., 2013b), and not being truly multi-objective. Although Kang and Lansey (2014) use a genetic algorithm as their optimization engine and indicate that their approach could be extended to include multiple objectives, this was not done in their paper.

The approaches presented in Ray et al. (2012), Housh et al. (2013) and Kang and Lansey (2014) do not include *formal* mechanisms for updating optimal sequences over time when new information about current and plausible future conditions becomes available. Consequently, these approaches can be considered to deal with deep uncertainty by way of "static robustness", which aims to reduce vulnerability under the largest range of plausible future conditions (Walker et al., 2013). However, given that optimal urban water supply augmentation sequence plans are generally developed over periods of 30-50 years, with augmentation options added incrementally over time (e.g. at 5- or 10-year intervals), there is likely to be significant benefit in developing an optimal sequencing approach that deals with deep uncertainty by way of "dynamic robustness", which considers adaptation over time as conditions change (Walker et al., 2013). It should be noted that although any of the above sequencing approaches could be applied using a sliding temporal window, and Kang and Lansey (2014) include an explicit flexibility criterion in their optimisation process and mentioned that their approach should be re-applied periodically, these adaptive mechanisms have not been *formalized* and their utility has not been *demonstrated*. The lack of the explicit application of an adaptive approach could at least in part be due to the difficulty of being able to test the adaptive mechanisms of such sequencing approaches, as adaptation needs to respond to changes in future conditions, which have not yet occurred and are therefore unknown. Consequently, there would be value in developing an experimental approach for testing the potential benefits of formal adaptive optimization approaches compared with currently used static approaches.

Given that existing multi-objective approaches to the optimal sequencing of water supply augmentation options are deterministic (e.g. Mortazavi-Naeini et al., 2014) and that existing optimal sequencing approaches that do consider uncertain future conditions are not multi-objective and do not include any *formal* mechanisms for adaptation, there is a need to develop a multi-objective, adaptive optimization approach for the sequencing of urban water supply augmentation options. However, as pointed out by Kwakkel et al. (2014), the use of dynamic adaptive plans, rather than static plans, represents an emerging planning paradigm for dealing with deep uncertainty. As such, implementation of this paradigm represents a major challenge, especially in terms of the development of computational methods that support the development of such plans, including consideration of transient scenarios (Kwakkel et al., 2014). This is particularly the case for the urban water supply augmentation problem, as infrastructure decisions are difficult to reverse and have long lifespans, making it difficult to develop dynamic, adaptive pathways. In addition, because of long lead times and large investments associated with urban water supply infrastructure, there is a need to ensure that water supply security is not compromised in periods between the implementation of augmentation options.

It follows that an adaptive approach to the optimal sequencing of urban water supply augmentation options is not simply a matter of re-applying an optimal static approach over a sliding window (see Szemis et al., 2014), but requires careful design so that it enables the identification of: (i) augmentation sequences that are both optimal for the long term, yet sufficiently flexible to be able to be adapted with minimal loss of optimality and (ii) augmentation options that are robust to changing conditions in periods between the implementation of augmentation options. In other words, such an approach should account for (i) dynamic robustness over the entire planning horizon, (ii) static robustness during those periods of the planning horizon when no changes can be made to the system, and (iii) pathways that are sufficiently flexible to cater to adaptation at minimal loss of optimality.

Consequently, the objectives of this paper are (i) to develop an formal optimal sequencing approach for urban water supply augmentation that is multi-objective and adaptive and (ii) to demonstrate the application of the approach to a case study based on the southern Adelaide water supply system in South Australia, including the development of an experimental approach that enables the potential benefits of adaptive approaches to be compared with currently used static approaches. The remainder of this paper is organized as follows. The proposed optimal sequencing approach is introduced in Section 4.2 and its application to the case study is described in Section 4.3. Results and discussion are presented in Section 4.4, followed by a summary and conclusions in Section 4.5.

4.2 Proposed Adaptive, Multi-objective Optimal Sequencing Approach

The philosophy underpinning the proposed approach is to add consideration of deep uncertainty to the traditionally used approach to obtaining optimal urban water supply augmentation sequences, which is based on the optimization of a set of objectives subject to the satisfaction of water supply security constraint(s). An approach based on this philosophy enables decision-makers to explore the impact of the consideration of deep uncertainty on optimal sequences of water supply augmentation options by identifying dynamic adaptive pathways, rather than a single optimal solution, which is in alignment with approaches based on adaptive dynamic planning (Haasnoot et al., 2013, Haasnoot et al., 2014, Kwakkel et al., 2014). This philosophy is also in keeping with that used in scenario-based decision-making, 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). This is in contrast to flexible optimal sequencing approaches that have been developed for water distribution system design (Basupi and Kapelan, 2013) and flood management (Woodward et al., 2014), in which uncertain future conditions are represented by probability distributions, thereby explicitly weighting the likelihood of different outcomes, rather than representing a set of alternative future states of the world (Mahmoud et al., 2009). Consequently, the proposed approach is more likely to be able to cater to deep uncertainty. However, it is acknowledged that the proposed approach also has a number of limitations, such as a potential loss of mathematical optimality, as discussed in Section 4.2.5.

In line with the underpinning philosophy outlined above, the proposed optimal sequencing approach for urban water supply augmentation under deep uncertainty consists of three steps (see Figure 4.1), namely: (i) identification of a *diverse portfolio* of optimal water supply augmentation sequence plans *over the entire planning period* with the aid of scenario-based multi-objective optimisation in order to identify solutions that are optimal under a range of plausible future conditions (catering to dynamic robustness over the entire planning horizon); (ii) assessment of the performance of the portfolio of optimal sequence plans in terms of *robustness* and *flexibility* over the *current staging interval* and *variation of the optimisation objectives* over the *entire planning period* (catering to static robustness during those periods of the planning horizon when no changes can be made to the system and to consideration of adaptation at a minimal loss of optimality); and (iii) selection of the water supply augmentation option(s) to be implemented at the *current decision stage* based on the trade-offs between the performance criteria in (ii). The above steps are repeated at subsequent decision stages (e.g. if the staging interval is 10-years, this process is repeated every 10 years) (Figure 4.1). Details of each of these steps are given in the following sections. It should be noted that the proposed approach could be easily adapted to other long-term water resources sequencing or scheduling applications.

4.2.1 Identification of Diverse Portfolio of Optimal Water Supply Augmentation Sequence Plans

When identifying a set of optimal solutions under deep uncertainty, it is critical to identify a portfolio of potential solutions that are able to respond to different future conditions (Korteling et al., 2013). In order to achieve this, it is proposed to use a formal multi-objective optimization approach to develop independent optimal sequence plans over the entire planning horizon (e.g. 50 years) for a number of scenarios representing different combinations of uncertain variables affecting future conditions. As shown in Figure 4.1 (Step 1a), the first step in the process involves the formulation of the optimization problem, including selection of the objectives to be optimized (e.g. minimize cost, minimize greenhouse gas emissions) ($O_{s(s=1\ to\ p)}$), selection of the planning horizon (i.e. the period over which optimal sequence plans are to be developed) (T), selection of the staging interval (i.e. the interval at which the addition of potential water supply augmentation options is considered) (t), selection of the water supply augmentation options (i.e. the decision variables) ($W_{k(k=1\ to\ n)}$) and definition of the constraint(s) (i.e. that some measure of supply is greater than or equal to some measure of demand, in addition to any constraints on the decision variables). The number of decision stages, y, can be calculated as $y=(T+t)/t$). It should be noted that it is suggested to only consider discrete water supply augmentation options, as this is what would generally be considered in practice.

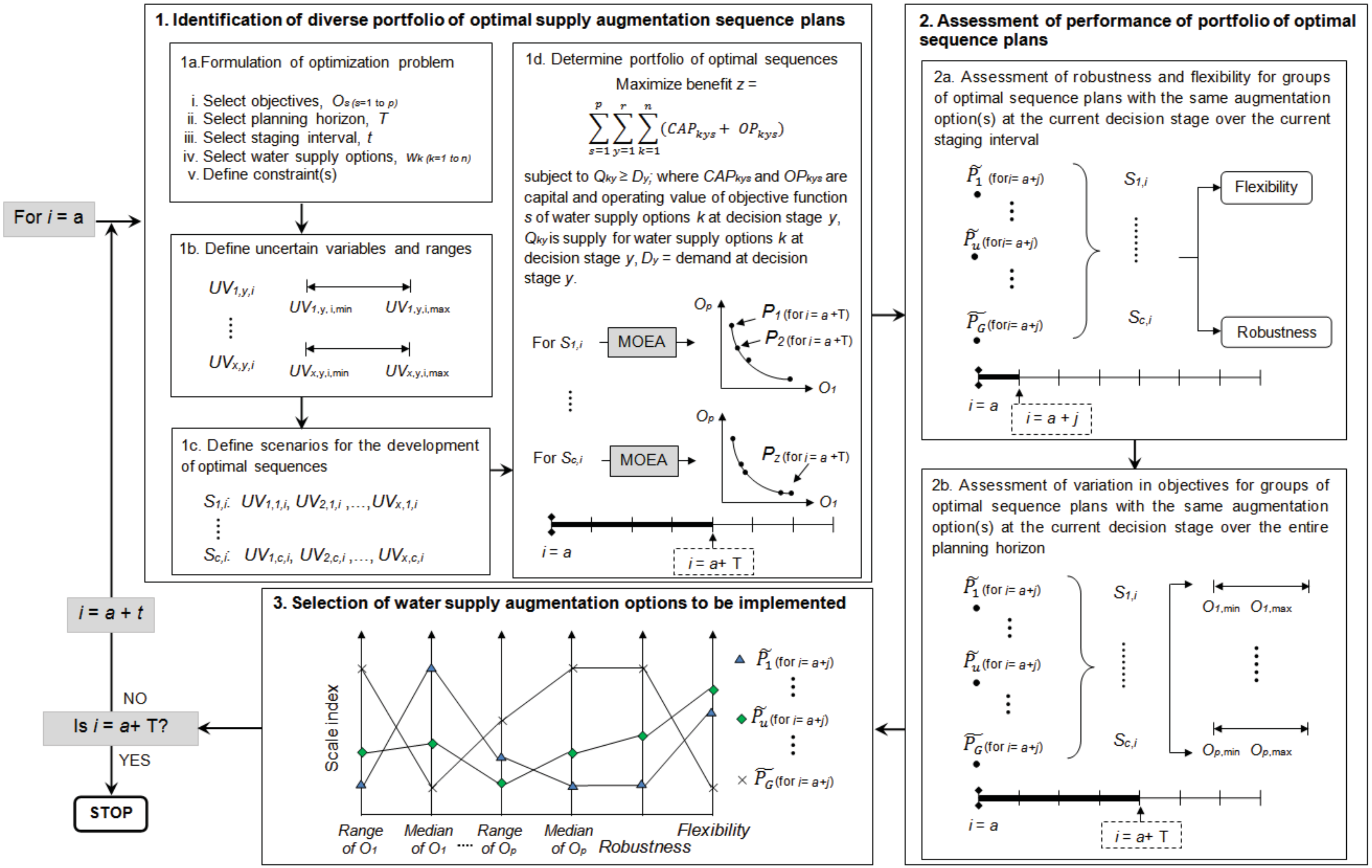

Figure 4.1 Diagrammatic representation of proposed adaptive, multi-objective optimal sequencing approach under deep uncertainty

Next, the uncertain variables need to be selected (UV_1, UV_2, … ,UV_x). As the optimization problem addressed here is the optimization of the selected objectives subject to supply being greater than or equal to demand, the critical uncertainties are in relation to the satisfaction of this constraint, and are therefore likely to be variables that affect supply and demand (e.g. rainfall, temperature, evaporation, population). As shown in Figure 4.1 (Step 1b), the ranges of the uncertain variables need to be defined for each of the decision stages y at the current time period i ($UV_{1,y,i}$, $UV_{2,y,i}$, … ,$UV_{x,y,i}$), followed by the selection of scenarios that consist of different combinations and values of the uncertain variables ($S_{1,i}$; $S_{2,i}$; …$S_{c,i}$) (Figure 4.1 (Step 1c)). It should be noted that the ranges of the uncertain variables, as well as the selection of the scenarios, should reflect current best knowledge in relation to the plausible changes of these variables over the planning horizon.

The use of scenario analysis is considered most appropriate for determining the portfolio of diverse solutions, as it enables alternative plausible future dynamic pathways to be developed in line with the philosophy that underpins the proposed approach, as outlined earlier. It should be noted that the different scenarios are not designed 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). For this reason, scenario analysis has been adopted widely as a means of assessing the impact of deep uncertainty in water resources planning (Kasprzyk et al., 2012, Kasprzyk et al., 2013b, Matrosov et al., 2013a, Matrosov et al., 2013b). Most scenario development involves people from different disciplines and organizations (Mahmoud et al., 2009) and can be achieved using informal (see e.g. Kasprzyk et al., 2012, Lany et al., 2013) or more formal (see e.g. Lempert and Groves, 2010, Matrosov et al., 2013b) approaches.

Once the problem has been formulated and the uncertain variables and scenarios defined, the portfolios of Pareto-optimal sequences over the entire planning horizon (i.e. from $i = a$ to $i = a+T$) can be obtained. As shown in Figure 4.1 (Step 1d), as part of the optimization process, the benefit associated with the capital (CAP) and operating (OP) values are maximized over the p objectives, y decision stages and n water supply options subject to the supply provided by the selected water supply options at a particular decision stage (Q_{ky}) being greater than or equal to the demand at that decision stage (D_y), as suggested by Beh et al. (2014).

For the optimisation engine, it is recommended to use multi-objective evolutionary algorithms (MOEAs). This is because they have proven to be flexible and powerful tools for solving complex water resources problems (Nicklow et al., 2010) and are able to identify solutions that represent multi-objective trade-offs in a single optimization run, without the need to provide relative weights for the various objectives. Additionally, EAs have been found to perform well in a number of urban water resources applications (Mortazavi et al., 2012, Cui and Kuczera, 2003, di Pierro et al., 2009). EAs can also be linked directly with simulation models of the water supply system under consideration, enabling interactions between different water sources to be taken into account, which is an important consideration (Matrosov et al., 2013b). Further details of the advantages of EAs are given in Maier et al. (2014).

As part of the optimization process, separate deterministic optimal sequence plans are generated over the entire planning horizon for each scenario (Figure 4.1 (Step 1d)), as was undertaken by Housh et al. (2013) and Kang and Lansey (2014). The objective function values of each sequence at each decision point are calculated with the aid of a simulation model of the resulting water supply system, which includes any existing, as well as the proposed, water supply sources. The simulation model is also used to check that supply is greater than or equal to demand throughout the planning horizon. Each staging interval of each sequence is simulated separately in order to cater to the potential incorporation of additional water supply options at each of the decision points. At the end of the optimization process, an approximation to the Pareto front (Pareto, 1896) of sequence plans for the scenario under consideration is obtained, which represents the best feasible trade-offs between the selected objectives. The solutions on the Pareto fronts for the different scenarios constitute the desired diverse portfolio of optimal water supply augmentation sequence plans (Figure 4.1 (Step 1d)).

4.2.2 Assessment of Performance of Portfolio of Optimal Sequence Plans

Even though it is important that optimal sequence plans are obtained over the *entire* planning horizon, decisions in relation to which options are *actually implemented* are only made for the *current* staging interval. For example, although optimal sequence plans might be developed for 40 years, if the staging interval is 10 years, only the first set of decisions of the 40 year plan is fixed now, while the rest of the plan can be *adapted* before the next set of decisions about which water supply augmentation option(s) to implement has to be made in 10 years' time. Consequently, the members of the portfolio of optimal sequence plans are grouped prior to performance assessment so that members of each group have the same augmentation option(s) at the *current* decision stage ($\tilde{P}_1, \tilde{P}_2, \ldots, \widetilde{P_u}, \ldots, \widetilde{P_G}$), where $\widetilde{P_u}$ is the u^{th} group of sequence plans that have the same augmentation options at the current decision stage, and *G* is the number of groups of optimal sequence plans with unique water supply augmentation options at the current decision stage (Figure 4.1 (Step 2)), which are determined by inspection of all optimal sequence plans. In this way, it is recognized that only decisions about which options to implement at the current decision stage need to be made at this time. However, optimality over the entire planning horizon is taken into account by only considering options at the current decision stage that are part of optimal sequence plans for the entire planning horizon. This concept of identifying optimal solutions over the planning horizon for different scenarios and focussing on the implementation of options at the first decision stage is similar to that followed by Housh et al. (2013) and Kang and Lansey (2014).

Although the optimal sequence plans that are part of a particular group have the same solution at the current decision stage, they have different solutions at subsequent decision stages, as they are drawn from different parts of the Pareto front (i.e. they represent different trade-offs between objectives) or from different Pareto fronts (i.e. they are optimal for different scenarios) and therefore represent different plausible future dynamic pathways that need to be assessed and explored. In order to achieve this, the performance of each of these pathways is assessed in terms of (i) the implications for water supply security until further changes can be made to the system (see Figure 4.1 (Step 2a – Robustness)), (ii) the implications on the ability to provide optimal solutions for different scenarios (see Figure 4.1 (Step 2a – Flexibility)), and (iii) the potential implications on objective function values (see Figure 4.1 (Step 2b)), as discussed in subsequent sections.

4.2.2.1 Assessment of robustness and flexibility over current staging interval

Robustness. The system that is fixed now will be exposed to uncertain conditions over the current staging interval (e.g. over the next 10 years). Consequently, although all current-stage augmentation options satisfy the constraint that supply is greater than or equal to demand for the scenario for which this option is optimal, to the degree to which water supply security of each of the unique current-stage solutions is adequate under all different scenarios until further changes can be made to the system needs to be assessed. This is achieved by assessing the static robustness of the different unique water supply augmentation options at the current decision stage (i.e. of the optimal sequence plans that form part of each of the groups, $\left(\tilde{P}_1, \tilde{P}_2, \dots, \widetilde{P_u}, \dots., \widetilde{P_G}\right)$ for all scenarios ($S_{1,i}$; $S_{2,i}$; $\dots S_{c,i}$) *over the current staging interval* (i.e. before there is an opportunity to make further changes to the system) (Figure 4.1 (Step 2a)).

In order to measure robustness, a number of different metrics can be used (Hashimoto et al., 1982a, Matrosov et al., 2013a, Matrosov et al., 2013b, Kasprzyk et al., 2013b, Korteling et al., 2013), all of which reflect some measure of insensitivity to future conditions and the ability to perform satisfactorily over a broad range of future conditions. As part of the proposed approach, the measure of Robustness used by Paton et al. (2014a, 2014b) is used:

$$Robustness_u = \frac{R_{uc}}{c} \tag{4.1}$$

where, R_{uc} is the number of scenarios for which group $\widetilde{P_u}$ of the optimal sequence plans is considered to exhibit acceptable performance over the current staging interval and c is the total number of uncertain scenarios. A desirable property of this measure of robustness is that it considers each scenario as an independent plausible future and provides information on the fraction of scenarios for which a particular solution performs at an acceptable level from a water supply security perspective. Which performance levels are considered acceptable are case study dependent, but could include potential water supply security measures such as reliability, resilience and vulnerability, as recommended by Yazdani et al. (2011), or the risk of water shortages, as suggested by Hall et al. (2012). It should be noted that, as the solutions at the current staging interval are identical for each of the groups of optimal sequence plans ($\widetilde{P_1}$, $\widetilde{P_2}$, …, $\widetilde{P_G}$), robustness only has to be calculated once for each group.

Flexibility. Given the adaptive nature of the proposed approach, the flexibility that the supply augmentation options that are fixed at the current decision stage provide in terms of being able to be part of optimal long-term sequence plans in the face of uncertain future conditions is also important. As stated in Mejia-Giraldo and McCalley (2014), a "solution is flexible when it can be adapted cost-effectively to *any* of the conditions characterizing the identified scenarios." From this perspective, a solution is more flexible if it is optimal for a larger number of scenarios and less flexible if is optimal for a smaller number of scenarios. Consequently, *Flexibility* is defined as the fraction of the scenarios for which group $\widetilde{P_u}$ solutions at the current decision stage are optimal as follows:

$$Flexibility_u = \frac{C_{p_u}}{c}$$

(4.2)

where, Cp_u is the number of scenarios for which a particular set of augmentation options(s), $\widetilde{P_u}$ is selected over the current staging interval, and c is the total number of uncertain scenarios. Therefore, a flexibility of 1 indicates that the solution that is fixed at the current decision stage is part of optimal sequence plans for *every* scenario and can therefore be part of optimal solutions under the full range of plausible future conditions considered. In contrast, a flexibility of $1/c$ indicates that the solution that is fixed at the current decision stage is only optimal for *one* of the c future scenarios. If this solution is implemented and the single scenario for which this solution is optimal does not occur, any changes to the sequence plan over the planning horizon will result in a loss of optimality, as another plan will be optimal. It should be noted that flexibility is calculated for each group of optimal sequence plans ($\widetilde{P_1}, \widetilde{P_2}, \ldots, \tilde{P}_u, \ldots, \widetilde{P_G}$) (see Figure 4.1 (Step 2a)).

4.2.2.2 Assessment of variation in objectives for the selected scenarios over the entire planning horizon

In addition to the assessment of robustness and flexibility of $\widetilde{P_u}$(i = 1, 2, …,G), it is important to consider the central tendency and spread of the objective function values of all of the different optimal sequence plans that are part of a group over all scenarios. In order to achieve this, it is proposed to use the *median* and *range* of the objective functions (O_1, O_2, …,O_p) over the entire planning horizon. It should be noted that the median and range are suggested as measures of central tendency and variation, rather than alternative measures, such as the expected value and standard deviation, as the scenarios represent different plausible futures, rather than events of a certain probability. In order to obtain the required values of median and range, the objective functions are calculated for each member of a particular group of optimal sequence plans over all scenarios. These calculations are repeated for each group of optimal sequence plans $\tilde{P}_u$(i = 1, 2, …,G) so that values of the median and range are obtained for each objective for each of the groups (see Figure 4.1 (Step 2b)).

4.2.3 Selection of Water Supply Augmentation Options to be Implemented

Finally, the most appropriate group of optimal sequence plans, and hence the water supply augmentation option(s) to be implemented at the current decision stage, needs to be selected. When dealing with multiple, competing objectives, there is generally no single optimal solution, but a collection of solutions that are all optimal (Pareto, 1896). This is because for these solutions, 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 (Cohon and Marks, 1975). Consequently, the solution to be implemented has to be selected based on user preferences of the trade-offs between the median and range of the objectives over the entire planning horizon (e.g. 50 years) and robustness and flexibility over the current staging interval (e.g. the next 10 years until further changes can be made to the system). It is suggested to use value path plots (Geoffrion et al., 1972) for this purpose, as they are a well-known method for visualising the trade-offs between performance measures (see Figure 4.1 (Step 3)).

It should be noted that the purpose of the proposed approach is not to suggest a single best solution, but to provide the best possible information on solutions that represent alternative future pathways to decision-makers. This is in line with other approaches that follow a similar philosophy as that underpinning the proposed approach (e.g. Kasprzyk et al., 2013b, Kwakkel et al., 2014). As mentioned above, selection of the option to be implemented is based on user preferences and should involve input from affected stakeholders. If the number of objectives (p) and the number of groups of optimal sequence plans with the same augmentation options at the current decision stage (G) is relatively small, this could be done informally. However, when the product of p and G is large, the use of more advanced visual analytics (see e.g. Kollat and Reed, 2007, Reed and Kollat, 2013), which is limited to about 6 or 7 options, or more formal decision-making processes, such as multi-criteria decision analysis (e.g. Hyde and Maier, 2006, Korteling et al., 2013) or scenario discovery (e.g. Kasprzyk et al., 2012, Lempert, 2013) approaches, for example, could be used. However, as mentioned above, the focus of this paper is not on the process for selecting the best option, but on the provision of information to decision-makers.

4.2.4 Adaptive Process

As part of the adaptive process, the general steps outlined in Sections 4.2.1 to 4.2.3 are repeated at each decision stage (i.e. every *t* years (e.g. every 10 years)) (see Figure 4.1– outer loop). However, there are some differences between decision stages, as illustrated in Figure 4.1 and summarized below.

1. As decision points are generally separated by some time (e.g. 10 years), the understanding of the trajectories of the various uncertain variables (e.g. population growth, climate futures) is likely to have changed from one decision point to the next. Consequently, the scenarios to be considered in the identification of the portfolio of optimal sequence plans (i.e. $S_{1,i}$; $S_{2,i}$; …$S_{c,i}$) are also likely to be different, as they should be developed based on best available knowledge at the time (see Section 4.2.1).
2. While the duration of the planning horizon (e.g. 50 years) remains unchanged, the actual start and end times of the planning horizon over which optimal sequence plans are developed with the aid of multi-objective evolutionary algorithms will be different (i.e. there will be different start and end points) (Figure 4.1).

4.2.5 Advantages and Limitations of Proposed Approach

Optimality versus practicality. As mentioned previously, the philosophy underpinning the proposed approach is to enable decision-makers to explore the impact of deep uncertainty on urban water supply augmentation sequences that are optimal with respect to the objectives and subject to meeting water supply security constraints, thereby presenting decision-makers with plausible future pathways. Consequently, the assessment of the impact of uncertainty on the water supply security constraint via the robustness measure and the assessment of the adaptability of selected solutions to different conditions via the flexibility measure are not included as additional objectives of the optimization problem, but are considered post-optimization. This is in line with other similar approaches to assessing water supply security under deep uncertainty that have not considered the sequencing of options (e.g. Kasprzyk et al., 2013b).

Apart from the philosophical reasons for not including robustness and flexibility as objectives stated above, there are also practical reasons, as the consideration of robustness and flexibility as objectives would increase the computational effort associated with the optimization considerably. This is because the calculation of robustness and flexibility for each solution at each iteration of the EA requires the results of the optimization runs for all scenarios. This would increase computational effort significantly, especially since the run-times associated with the integrated model of the water resources system can be quite long. Furthermore, repeated model runs with different stochastically generated hydrological inputs are required in order to obtain a rigorous assessment of water supply security (see Mortazavi et al., 2012), thereby increasing run-times even further.

Despite the advantages outlined above, consideration of robustness and flexibility post-optimization, rather than as objectives in the optimization problem, can also be considered a limitation, as this could result in solutions with reduced robustness and flexibility, since these measures are not optimized. In other words, the proposed approach identifies the relative robustness and flexibility of solutions that are optimized for the objectives, but does not necessarily identify solutions that are optimally robust and flexible. However, for the urban water supply augmentation problem and robustness measure considered here, the solution for the worst case scenario will, by definition, always have a robustness of 1 (i.e. the largest possible, and hence optimal, value). Nevertheless, identification of the best possible trade-offs between robustness and the other performance measures are not guaranteed. In relation to flexibility, an alternative measure, such as regret costs (see Kang and Lansey, 2014), could have been used and included more formally in the optimization process, thereby improving the mathematical optimality of the solutions. However, such an approach would be geared towards identifying a single optimal solution, rather than presenting decision-makers with alternative pathways.

The approach of presenting decision-makers with different future pathways by obtaining separate optimal solutions for each scenario could also result in a loss of mathematical optimality, as a solution that is optimal for a particular scenario might not be optimal if all scenarios are considered simultaneously, as was done by Kang and Lansey (2014). However, it should be noted that the flexibility criterion introduced in this paper provides an indication as to whether or not this is the case. For example, if the flexibility criterion is equal to 1, then there is no loss of optimality, as a particular solution is optimal across all scenarios. In contrast, if the flexibility is less than 1, there will be some loss of optimality. However, the magnitude of this loss cannot be quantified in terms of objective function values using this criterion. It should also be noted that as Kang and Lansey (2014) used a compromise cost function to obtain an optimal solution across all scenarios, rather than presenting alternative pathways to decision-makers, there is likely to be a trade-off between achieving mathematical optimality and presenting options to decision-makers.

Another factor that could result in a loss of mathematical optimality is the fact that the proposed approach uses discrete values of the water supply augmentation options. However, from a practical perspective, urban water supply augmentation options are generally discrete in nature (e.g. whether to implement a particular augmentation option or not or what capacity a particular augmentation option should be), so this is unlikely to present any problems from a practical perspective.

Single objective versus multi objective. As mentioned previously, compared with other approaches to solving similar problems (Kang and Lansey, 2014, Housh et al., 2013, Ray et al., 2012), the proposed approach is multi-objective, which is an advantage, given that most practical problems have more than one objective. Although Kang and Lansey (2014) used an EA as their optimization engine, thereby enabling their approach to be expanded to be multi-objective, this extension has not yet been reported or tested in the literature.

However, the proposed approach also presents a number of challenges due to its multi-objective nature. Firstly, there could be multiple sequence plans with the same solution at the current staging interval that are on the Pareto front for a particular scenario. In this case, only the presence or absence of this solution on Pareto fronts for different scenarios is taken into account in the calculation of flexibility (4.2), not the number of optimal sequence plans with this solution, and hence potential losses in trade-off information are not considered in the proposed flexibility criterion. Secondly, as the number of scenarios for which particular sequence plans are optimal varies, some sequence plans that are Pareto optimal for a particular scenario might be completely dominated in terms of the median and range of the objective function values once the solution has been evaluated over all scenarios, for some of which a solution might not be Pareto optimal. However, this is not a problem from a practical perspective, as such solutions can be discarded as part of the final evaluation process.

4.3 Case Study

4.3.1 Background

In order to illustrate and test the utility of the proposed approach, it is applied to a case study based on the southern region of the Adelaide water supply system (WSS) in 2010. Adelaide is the capital city of South Australia (SA) (see Figure 4.2) and has a 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. 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, 2009b).

This case study is selected as it has been used as a benchmark in previous water resources studies. Paton et al. (2013) assessed the impact of climate change on the water supply security of this system and concluded that supply augmentation was needed. Paton et al. (2014a) assessed the utility of a small number of water supply augmentation options in terms of PV of cost and water supply security and Paton et al. (2014b) used a multi-objective optimization approach to explore the trade-offs between PV of cost, PV of greenhouse gas emissions and water supply security for different supply augmentation options and operating policies. However, the *sequencing* of water supply augmentation options was not considered in any of these studies. The optimal sequencing problem for this system was addressed by Beh et al. (2014), but they used an approximate problem formulation in conjunction with a linear programming method, did not use a truly multi-objective approach and did not consider the impact of uncertainty (i.e. the optimal sequencing problem was considered to be deterministic).

The southern Adelaide WSS (see Figure 4.2) supplies around 50% of the demand of metropolitan Adelaide. In 2010, the system was supplied by 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 from the River Murray is based on a 5-year rolling license for Adelaide, which is fixed at 650GL. Of this, half is assumed to be allocated to the southern Adelaide WSS. The Happy Valley reservoir is a service reservoir that stores water transferred from Mount Bold reservoir prior to treatment at the Happy Valley water treatment plant.

As highlighted by Paton et al. (2013), supply augmentation is required for the southern Adelaide WSS to meet future demands in the face of increased water demand and climate change impacts. In this study, the potential augmentation options identified by the SA government are considered, including a desalination plant at Port Stanvac, various stormwater harvesting schemes, and household rainwater tanks (Figure 4.2) (Government of South Australia, 2009b). It should be noted that long-term demand management options have already been applied extensively in the case study system and are therefore not considered. However, supply shortfalls that can be accommodated by temporary water restrictions are included as part of the acceptability criterion for the robustness calculations (see Section 4.3.3.2). Augmentation of existing sources is also excluded as options, as there is limited potential for additional supply from these sources.

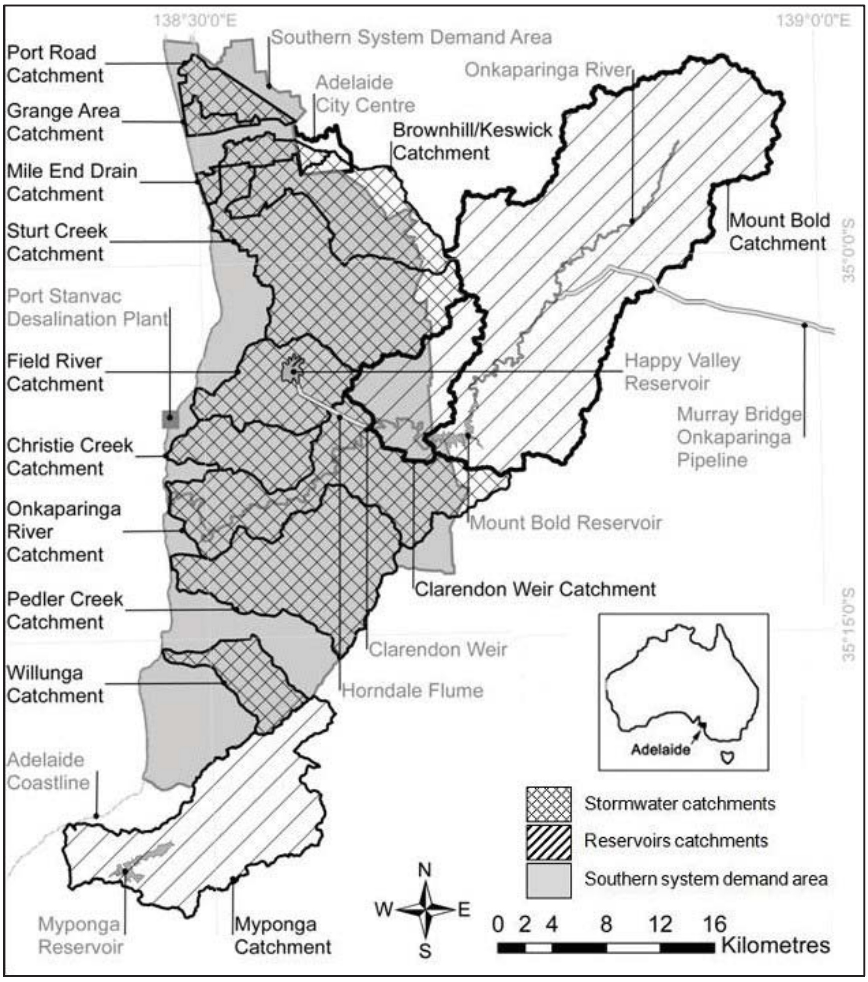

Figure 4.2 Map of the Southern Adelaide water supply system (WSS).

4.3.2 Overall Experimental Approach

In line with the objectives stated in Section 4.1, the overall purpose of the experimental approach is to demonstrate the application of the proposed approach to the Adelaide case study and to test the utility of the adaptive features of the proposed approach by comparing its performance with that of an equivalent static approach. A summary of the overall experimental approach is given in Figure 4.3. Part A in Figure 4.3 corresponds to the application of the proposed approach to the Adelaide case study and is aligned with the general approach introduced in Section 4.2 (Figure 4.1). Part B in Figure 4.3 corresponds to the assessment of the utility of the adaptive features of the proposed approach by comparison with an equivalent static approach.

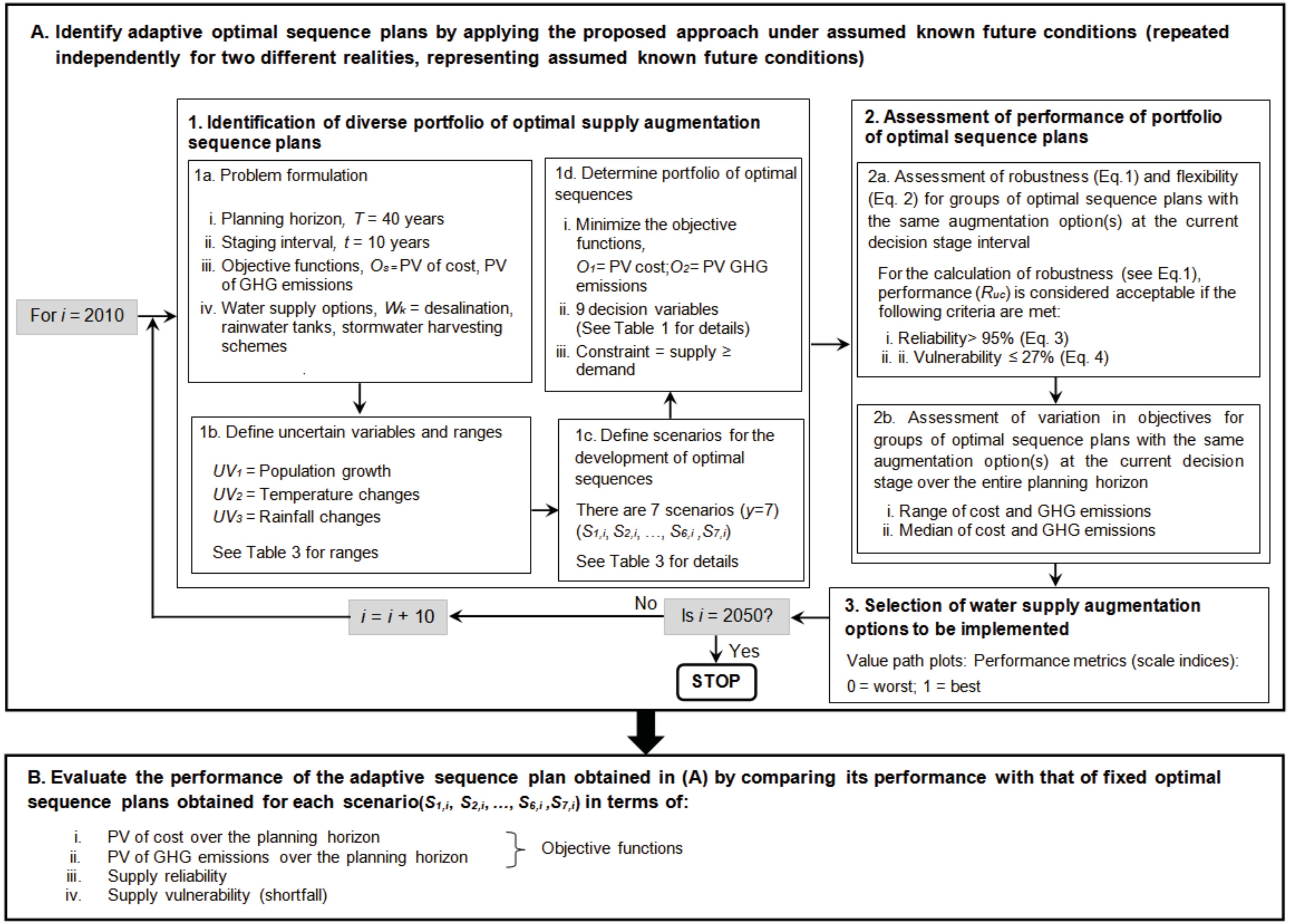

Figure 4.3 Summary of experimental approach for the Adelaide case study

As it is only possible to evaluate the true utility of the adaptive nature of the proposed approach over the actual duration of the planning horizon (e.g. over the next 40 years), the proposed experimental approach is based on assumed known future conditions (or simulated realities) and the simulation of what would actually happen over the adopted planning horizon under these conditions (Figure 4.3, Part A). In other words, steps 1 to 3 of the proposed approach (Figure 4.1 and Figure 4.3, Part A) are implemented at 2010 to determine which supply augmentation option(s) to implement at this time. Next, it is assumed that 10 years have passed and that it is known what the actual values of the uncertain variables at this time are and that the corresponding updated estimates of the ranges of the uncertain variables and scenarios are known. Steps 1 to 3 of the proposed approach are then repeated to determine which supply augmentation option(s) to implement at the simulated current time (i.e. 2020). This whole process is then repeated for 2030, 2040 and 2050 for a particular reality in accordance with the adaptive nature of the proposed approach (Figure 4.1 and Figure 4.3, Part A).

In order to demonstrate that the proposed adaptive approach results in different augmentation options under different sets of actual future conditions, the entire process in Part A. of Figure 4.3 is repeated for a different set of assumed known future conditions. These two sets of assumed known future conditions are referred to as Reality 1 and Reality 2. In other words, two sets of independent results are presented for two alternative simulated realities for the sake of comparison of how different augmentation options can be obtained by using the adaptive approach based on different changes in actual future conditions. It should be noted that the realities are different from the scenarios. Whereas the realities represent actual known future conditions (i.e. what has actually happened), which are assumed for the purposes of the computational experiments for testing the utility of the adaptive features of the proposed approach presented in this paper (Part B, Figure 4.3), the scenarios represent plausible future conditions at the time of decision making and are an integral part of the proposed approach (Part A, Figure 4.3).

In order to assess the utility of the adaptive nature of the proposed approach, the augmentation options obtained using the proposed adaptive approach are compared with an equivalent static approach (e.g. Mortazavi-Naeini et al., 2014), as all current approaches to the optimal sequencing of urban water supply augmentation options are not adaptive, as discussed in Section 4.1 (Figure 4.3, Part B). Consequently, the static approach provides a benchmark of current best practice in literature against which to assess the adaptive features of the proposed approach. The static approach is implemented for each of the plausible scenarios to provide a comprehensive basis of comparison.

The comparison of the adaptive and static approaches is conducted over the two independent realities. As the purpose is to assess how well the sequence plans obtained using the proposed adaptive approach and the benchmark static approach perform under the two realities, and not which approach performs best for a given reality, the performance metrics for a particular sequence are averaged over the two realities. This enables the performance of a selected sequence to be assessed in the face of the occurrence of two different actual future conditions, which are unknown at the time of decision-making.

Details of the implementation of the above approach for the case study based on the southern Adelaide WSS are given in the subsequent sections, with Part A of Figure 4.3 corresponding to Section 4.3.3 and Part B to Section 4.3.4.

4.3.3 Identification of Optimal Sequence Plans

The details for steps 1 to 3 of the proposed approach (Figure 4.1) for the Adelaide case study are summarized in Part A. of Figure 4.3 and described below. As mentioned above, this process is repeated for each of the two independent realities for the sake of assessing the utility of the adaptive features of the proposed approach.

4.3.3.1 Identification of diverse portfolio of optimal supply augmentation sequence plans.

Problem Formulation (Figure 4.3, Part A, Section 1a). A 40 year planning horizon and a ten year staging interval are adopted. Therefore, there are five decision stages over the 40 year planning horizon (i.e., 2010, 2020, …, 2050). However, as these years correspond to the first year of the 40 year planning horizon, a total time period of 80 years is considered (i.e. 2010-2050, 2020-2060, …, 2050-2090).

The selected objectives include the minimization of the present value (PV) of economic cost and the PV of greenhouse gas (GHG) emissions. GHG emissions are considered as an objective in addition to the most commonly used objective of cost minimization due to an increased awareness of the need to reduce the carbon footprint associated with water supply systems (Wu et al., 2010b, Paton et al., 2014b, Wu et al., 2010a). GHG emissions are of particular concern for the southern Adelaide system because water is pumped significant distances from the River Murray and because desalination is considered as an alternative source of water (see

Paton et al., 2013, Paton et al., 2014b, Paton et al., 2014a, Beh et al., 2014). Note that gross GHG emissions are used in this study. These may be fully or partially offset by the purchase of green power or other carbon offsets.

Both the PV of cost and the PV of GHG emissions consist of two components, namely capital and operating values. Capital costs and GHG emissions are incurred at the construction phase of a project (e.g. materials and outlay), whilst operating values are incurred over the life of a project (e.g. electricity for pumping and maintenance). A discount rate of 6% is used for the calculation of the PV of cost, as suggested by Wu et al. (2010a). In contrast, a discount rate of 1.4% is used for the calculation of the PV of GHG emissions, as this has been suggested as being appropriate for stabilizing GHG concentrations in the atmosphere within a desired range (Wu et al., 2010b). The capital emissions values are computed using embodied energy (Treloar, 1995) and emission factor analysis (Wu et al., 2010a). Further details are provided in Beh at al. (2014) and Paton et al. (2013, 2014b, 2014a).

The existing water supply options (i.e. the three reservoirs and supply from the River Murray) are included in all sequence plans 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 point.

The production capacity of the Port Stanvac desalination plant is either 50 or 100 GL per annum, with the option of a 50GL per annum expansion of the 50GL per annum plant. Thus, either a 50GL or a 100GL desalination plant can be selected at any of the decision stages, but not both, and the selected desalination plant cannot be down-sized at later stages. It should be noted that the desalination plant can supply the entire metropolitan Adelaide region, so it is assumed that 50% of its capacity can supply the southern Adelaide WSS. Once one of the desalination options has been selected, it cannot be selected again. However, if the 50GL desalination plant is selected, expansion to full capacity is allowed at one of the subsequent decision points.

The stormwater harvesting schemes considered include Brownhill and Keswick Creek, Sturt River, Field River and Pedler Creek (Figure 4.2). The potential supply from these schemes is generally different from year to year as a result of hydrologic variability, but their estimated annual yields range from 1.6 to 7.0 GL/year (Beh et al., 2014). One or more of the schemes can be selected at any of the decision stages. However, each scheme can only be selected once. The amount of water supplied by each scheme during each decision stage is calculated using a simulation model and is a function of rainfall and the interaction with the other selected sources.

Ten potential rainwater tank capacities are considered, ranging from 1 to 10kL. The potential supply from these tanks is generally different from year to year as a result of hydrologic variability, but their estimated annual yields range from 35 to 47.1 kL/tank/year (Beh et al., 2014). It is assumed that rainwater tanks with a particular capacity can be implemented at any of the decision stages. However, the option to use rainwater tanks as a source can only be selected once during the planning horizon. 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.

As the quality of the stormwater and rainwater is generally not of drinking standard, these sources are assigned to non-potable uses, whereas supply from the reservoirs and the desalination plant is chosen to provide household indoor use. Further details of the mapping of sources to end-uses and how this was represented in the simulation model are given in Beh et al. (2014) and Paton et al. (2014b, 2014a)

The decision variables corresponding to the sequencing of the above augmentation options used during the optimization are summarised in Table 4.1. The estimated yield, capital and unit operating costs and GHG emissions of each water supply options are also given in Table 4.1 (see Beh et al., 2014). However, these are only estimates and the actual values supplied by each source are calculated with the aid of a simulation model for a particular scenario at a particular decision stage based on the interaction of the different potable and non-potable demands and the selected mix of supply sources. As the capacities of most of the water supply options are fixed (i.e. desalination, stormwater harvesting schemes), the discrete decision variables correspond to the decision stage at which a particular option is implemented, ranging from 0 (i.e. the option is not implemented over the planning horizon) to 5 (i.e. the option is implemented at decision stage 5) (decision variables 1-4 and 6-9, Table 4.1). However, in addition to a decision variable for timing, rainwater tanks also have an integer decision variable corresponding to rainwater tank capacity (decision variable 5, Table 4.1), 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 with time due to changes in population.

Table 4.1 Details of decision variable formulation

Decision variable	Description	Lower limit	Upper limit	Estimated yield	Capital cost ($)	Unit operation cost ($/kL)	Capital GHG emissions ($kgCO_2$-e)	Unit GHG emissions ($kgCO_2$-e/kL)
1	50GL desalination plant implementation stage	0	5	25.0 GL/year	1,347,000,000	1.00	228,538,000	5.41
2	100GL desalination plant implementation stage	0	5	50.0 GL/year	1,830,000,000	1.00	237,103,000	5.43
3	50GL desalination plant expansion implementation stage	0	5	25.0 GL/year	483,000,000	1.00	8,565,000	5.41
4	Household rainwater tank implementation stage	0	5					
5	Household rainwater tank size (kL)	1	10	35.0 – 47.1 kL/year	2,181 – 3,560	0.63 - 0.78	718 – 4,635	1.22
6	Brownhill & Keswick Creek stormwater harvesting scheme implementation stage	0	5	6.3 GL/year	160,025,000	1.23	7,249,000	2.04
7	Sturt River stormwater harvesting scheme implementation stage	0	5	7.0 GL/year	194,193,000	1.23	7,351,000	2.06
8	Field River stormwater harvesting scheme implementation stage	0	5	1.6 GL/year	35,689,000	1.23	3,576,000	6.05
9	Pedler Creek stormwater harvesting scheme implementation stage	0	5	5.0 GL/year	110,682,000	1.23	5,643,000	1.60

Definition of uncertain variables and scenarios (Figure 4.3, Part A, Section 1b,c). Population, rainfall and temperature are considered as the uncertain variables ($UV_{1,i}$; $UV_{2,i}$; $UV_{3,i}$) as they have a direct impact on supply and demand. As mentioned in Section 4.3.2, in order to illustrate the benefit of the adaptive nature of the proposed approach, it is applied to two realities, each consisting of different known trajectories of the uncertain variables up to 2050. Reality One has a milder and Reality Two a more severe impact on water supply security in terms of total demand and climate change conditions (see Table 4.2). The changes in population growth and climate change impact used in the two realities are based on estimates from the Government of South Australia (2009b) and Australian Bureau of Statistics (2013) to ensure they are plausible.

Table 4.2 Details of the two realities (assumed known future conditions) considered (cumulative changes relative to 2010)

	2020	2030	2040	2050
Reality 1				
Population growth	7%	13%	18%	22%
Climate change impact:				
1. Changes in temperature (°C)	0.25	0.55	0.70	1.00
2. Changes in rainfall	-0.5%	-1.5%	-4.0%	-6.0%
Reality 2				
Population growth	7%	18%	20%	29%
Climate change impact:				
1. Changes in temperature (°C)	0.25	0.60	1.00	1.25
2. Changes in rainfall	-0.5%	-3.0%	-6.0%	-9.0%

For each reality, seven scenarios ($S_{1,i}$; $S_{2,i}$; …$S_{7,i}$) consisting of different population growth and climate change impacts are used to represent a small number of plausible, but different, future pathways. Scenario 1 represents the best set of plausible future conditions in terms of water supply security with extremely low projected population growth and the least severe future climate change impact. In contrast, Scenario 7 represents the worst set of plausible future conditions with respect to water supply security, with extremely high projected population growth and severe climate change impact. These extremes are considered to ensure the generation of Pareto-optimal solutions that can cater to a wide range of plausible future conditions. Details of the ranges of the uncertain variables for each of the seven scenarios for each of the two realities, representing assumed best knowledge at the time of interest, are given in Table 4.3. As can be seen, the ranges of the uncertain variables for the different scenarios change over time, thereby representing transient scenarios, as advocated by Haasnoot et al. (2013) and Kwakkel et al. (2014).

The seven population scenarios for each reality are based on an initial population of 600,240 for the southern Adelaide region in 2010 (Australia Bureau of Statistics, 2011). For each reality, the seven time series of population projections are based on 40 year annual population projections accounting for various assumptions of fertility, mortality, net interstate migration and net overseas migration (Australia Bureau of Statistics, 2013).

The seven rainfall and temperature scenarios for each reality are based on different combinations of SRES scenarios (A1FI, A1T, A2, B1, B2) and Global Circulation Models (GCMs) (CCSM3, CGCM3.1, CSIRO-MK3.5, FGOALS-g1.0, MIROC3.2 (hires), MIROC3.2 (medres), and MRI-CGCM2.3.2), as suggested by Paton et al. (2013) for the case study area. Based on the outputs of different combinations of SRES scenarios and GCMs, the climate change impacted daily rainfall and evaporation data are obtained by multiplying the 40 year historical rainfall and evaporation data used in the simulation model by the appropriate climate change factor obtained from OzClim (http://www.csiro.au/ozclim/), as was undertaken by Paton et al. (2013) for the case study area.

As discussed in Section 4.2.1, in practice, the scenarios would be developed with the aid of stakeholders with different backgrounds and from different organizations. However, in this case, the above scenarios are assumed for the sake of illustration of the proposed approach. However, the scenarios are selected carefully to represent a range of plausible and very different future conditions. In addition, the different scenarios are not necessarily equally likely, as some represent combinations of extreme conditions, while others do not.

Table 4.3 Uncertain variable options for each scenario and reality (cumulative changes relative to the starting year)

	2010 -2050			2020 - 2060			2030 - 2070			2040 - 2080			2050 - 2090		
	Population growth (%)	Temperature change (°C)	Rainfall change (%)	Population growth (%)	Temperature change (°C)	Rainfall change (%)	Population growth (%)	Temperature change (°C)	Rainfall change (%)	Population growth (%)	Temperature change (°C)	Rainfall change (%)	Population growth (%)	Temperature change (°C)	Rainfall change (%)
Reality 1															
Scenario 1	-2.80	0.80	-7.60	-1.20	0.94	-7.70	-13.60	1.06	-8.60	-35.20	1.16	-9.30	-69.20	1.25	-10.00
Scenario 2	8.00	0.80	-7.60	16.40	0.94	-7.70	13.20	1.06	-8.60	-20.00	1.16	-9.30	-18.40	1.25	-10.00
Scenario 3	18.80	1.09	-9.90	17.20	1.31	-10.40	9.20	1.52	-11.80	-26.40	1.66	-12.80	-21.60	1.71	-13.10
Scenario 4	29.60	1.09	-9.90	8.40	1.31	-10.40	9.60	1.52	-11.80	6.80	1.66	-12.80	0.00	1.71	-13.10
Scenario 5	40.80	1.09	-9.90	20.00	1.31	-10.40	32.00	1.52	-11.80	38.80	1.66	-12.80	41.20	1.71	-13.10
Scenario 6	51.60	1.29	-11.60	30.80	1.41	-11.90	52.00	1.57	-12.20	66.80	1.72	-13.10	76.80	1.91	-14.30
Scenario 7	62.80	1.29	-11.60	34.00	1.41	-11.90	58.00	1.57	-12.20	75.60	1.72	-13.10	88.40	1.91	-14.30
Reality 2															
Scenario 1	-2.80	0.93	-9.40	35.20	1.08	-10.80	61.20	1.22	-12.00	81.20	1.33	-13.00	97.60	1.44	-13.90
Scenario 2	8.00	0.93	-9.40	38.40	1.08	-10.80	67.20	1.22	-12.00	90.00	1.33	-13.00	108.80	1.44	-13.90
Scenario 3	18.80	1.26	-12.30	39.20	1.51	-12.50	70.00	1.75	-13.70	96.00	1.92	-14.40	118.40	1.97	-14.80
Scenario 4	29.60	1.26	-12.30	40.00	1.51	-12.50	73.20	1.75	-13.70	102.40	1.92	-14.40	128.00	1.97	-14.80
Scenario 5	40.80	1.26	-12.30	42.80	1.51	-12.50	77.60	1.75	-13.70	107.20	1.92	-14.40	133.20	1.97	-14.80
Scenario 6	51.60	1.49	-14.30	45.60	1.63	-15.50	81.60	1.81	-16.50	112.00	1.98	-17.80	138.40	2.19	-18.30
Scenario 7	62.80	1.49	-14.30	51.60	1.63	-15.50	96.80	1.81	-16.50	138.00	1.98	-17.80	176.80	2.19	-18.30

Determination of portfolio of optimal sequences (Figure 4.3, Part A, Section 1d). *WaterCress* (*Water* - *C*ommunity *R*esource *E*valuation and *S*imulation *S*ystem) is used as the simulation model for calculating the objective functions and checking demand constraints. *WaterCress* is a water balance model that enables simulation of a real life layout of a water supply system as an assembly of its components. Each component has an associated database which 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, and (iii) can incorporate less conventional water supply sources (e.g. desalination and recycled water). Furthermore, the model is freely available and was developed specifically for South Australian conditions. Further details of the *WaterCress* model developed for the case study WSS are given in Beh et al. (2014) and Paton et al. (Paton et al., 2014b).

Total demand is calculated as a function of population size, per capita demand and commercial and industrial demand. Population is considered as one of the uncertain variables, as detailed above. Average household size is assumed to be constant at 2.3 people and per capita demand is held constant at 491 L/p/day over the planning horizon (see Beh et al., 2014), as variability in population has been shown to have by far the greatest impact on water supply security for this system (Paton et al., 2013).

For each of the two realities, the multi-objective optimization process is repeated for each scenario at each of the five decision points. The Water System Multiobjective Genetic Algorithm (WSMGA) (Wu et al., 2010b) is used as the optimisation engine, as it is based on the widely used multiobjective genetic algorithm NSGA-II (Deb et al., 2002), is able to cater to integer decision variables and has been used successfully in a number of multi-objective optimisation studies of water systems (Wu et al., 2010a, Wu et al., 2010b, Wu et al., 2013, Paton et al., 2014a). In order to obtain the best possible values of the parameters controlling GA searching behaviour, a number of preliminary trials are conducted. The optimal values are found to be a population size of 150, a probability of cross-over of 0.9 and a probability of mutation of 0.1. Hypervolume convergence is used as the termination criterion, as this is one of the most popular measures for capturing the diversity, as well as the convergence, of solutions in multi-objective optimization problems (Zitzler, 1999, Reed et al., 2013).

4.3.3.2 Assessment of performance of portfolio of optimal sequence plans.

For a particular reality and decision stage, all solutions on the Pareto fronts for the seven scenarios are analysed and grouped so that each group contains the same augmentation option(s) at the current staging interval (see Section 4.2.2) and all solutions in each of these groups are assessed in terms of robustness, flexibility and variation of the median and range of the PV of cost and PV of GHG emissions over all scenarios, as detailed below.

Assessment of robustness and flexibility (Figure 4.3, Part A, Section 2a). Robustness is calculated in accordance with Equation 4.1 (see Section 4.2.2). In Equation 4.1, the performance of the water supply system is considered acceptable when reliability (4.3) is greater than 95% and the maximum vulnerability (4.4) is less than or equal to 27% of demand. This latter figure is equal to the projected savings under Adelaide's highest Level 5 water restrictions (Chong et al., 2009).

As suggested by Beh et al. (2014) and Paton et al. (2014a, 2014b) hydrologic variability is accounted for by using 20 replicates of daily stochastic rainfall for each rainfall station. These stochastic rainfall series are generated for each scenario using the Stochastic Climate Library (SCL) (www.toolkit.net.au/scl). Further details of the generation of the stochastic rainfall time series are given in Paton et al. (2013) and Beh et al. (2014). Consequently, the reliability and vulnerability values used in the robustness calculations are the average values obtained for the 20 stochastic rainfall sequences for the next staging interval as follows.

$$Reliability = \frac{\sum_{k=1}^{m}\left[\left(\frac{T_s}{T_i}\right)\right]_k}{m}$$

(4.3)

where, T_s is the number of years for which supply meets demand, T_i is the length of the selected staging interval (years), and m is the number of stochastic sequences.

$$Vulnerability = \frac{\sum_{k=1}^{m}\left[maximum\left(\frac{D_y}{S_y}\right)\right]_k}{m}$$

(4.4)

where, D_y is the volume of annual supply shortfall, as obtained from the *WaterCress* model, and S_y is the total annual demand, as obtained from the *WaterCress* model.

Assessment of variation in objectives (Figure 4.3, Part A, Section 2b). The median and range of the PV of cost and the PV of GHG emissions are obtained by calculating the PV of cost and PV of GHG emissions for all Pareto optimal solutions for all scenarios and calculating the required statistics for all solutions belonging to a particular group (i.e. with the same solution at the current staging interval). This is achieved with the aid of the *WaterCress* model.

4.3.3.3 Selection of water supply augmentation options to be implemented (Figure 4.3, Part A, Section 3).

The water supply augmentation option(s) to be implemented at a particular decision stage are selected based on informal consideration of the trade-offs between the performance metrics (i.e. robustness, flexibility, median and range of PV of cost and median and range of PV of GHG emissions), as illustrated in value path plots. It should be noted that all indices of the performance metrics are scaled from zero to one, where one is the best and zero the worst value.

It should be noted that in practice, more formal decision-making processes are likely to be used, including stakeholder input and a clear articulation of the relative importance of the criteria, potentially using some of the methods mentioned in Section 4.2.3. However, this is not been undertaken here, as the main purpose is to illustrate the information obtained by applying the proposed approach and the selection of options has been made by weighing up the trade-offs between the assessment criteria.

4.3.3.4 Application to different decision stages under different realities (known future conditions).

As shown in Figure 4.3, steps 1 to 3 outlined in Section 4.3.3.1 to 4.3.3.3 are implemented for 5 decision stages starting at 2010, 2020, 2030, 2040 and 2050, using the different scenarios outlined in Table 4.3. The entire process is also repeated for the two independent realities, as explained earlier (see Table 4.2 and Table 4.3) for the purpose of being able to simulate the performance of the proposed approach under different actual conditions and enabling the assessment of the utility of the adaptive features of the proposed approach.

4.3.4 Evaluation of Adaptive Optimal Sequence Plans (Figure 4.4, Part B)

As mentioned in Section 4.3.2, in order to assess the utility and potential benefits of the proposed adaptive approach, the *actual* performance of the optimal *adaptive* sequences obtained for the two realities is compared with that of *static* optimal sequences obtained for the different scenarios at the beginning of the planning horizon in terms of optimization objectives and *actual* water supply security (i.e. reliability and vulnerability). It should be noted that for each of the optimal sequence plans, the NPV of cost and GHG emissions are calculated for the entire planning horizon (as there is a single plan), while reliability and vulnerability are calculated for each staging interval, as they change over the planning horizon as different augmentation options come online. In accordance with the overall approach outlined in Section 4.3.2, the overall performance of the sequences obtained using the proposed adaptive and the benchmark static approaches is compared by averaging the performance measures over the two realities.

4.4 Results and discussion

The results are presented in two sections, including an illustration of the development of the adaptive optimal sequence plans for a single time step (Part A of Figure 4.3 - Section 4.4.1) and the evaluation of the utility of the adaptive features of the proposed approach (Part B of Figure 4.3 – Section 4.4.2).

4.4.1 Development of Adaptive Optimal Sequence Plans

In this section, the results for each of the three major steps of the proposed approach (i.e. Steps 1, 2 and 3 in Figure 4.1 and 3A) are presented for the first decision stage (i.e. 2010) for illustration purposes (Section. 4.4.1.1 to 4.4.1.3). The optimal sequences obtained by simulating application of the proposed approach over an actual period of 40 years (i.e. from 2010 to 2050) for the two different realities are presented in Section 4.4.1.4. The optimal augmentation options for 2020, 2030, 2040 and 2050 for both realities are based on the types of results presented in Section. 4.4.1.1 to 4.4.1.3, which are included as supplementary material. It should be noted that in real life, an optimal sequence, such as that presented in Section 4.4.1.4, would be developed over 40 years, with application of the three steps in the proposed process and analysis of the results occurring every 10 years, resulting in the selection of the augmentation option(s) to implement at the current decision stage. In practice, there would only be a single reality and the two different realities are simulated here for the purposes of assessing the utility of the adaptive features of the proposed approach, as explained previously.

4.4.1.1 Identification of diverse portfolio of optimal sequence plans (2010-2050)

The Pareto fronts of optimal sequence plans for the seven scenarios for 2010-2050 are shown in Figure 4.4. As can be seen, the optimal augmentation sequences required to ensure supply is greater than or equal to demand for the seven scenarios result in significant differences in the PV of cost and the PV of GHG emissions. This is as expected, as greater supply augmentation is required for the scenarios that include greater population growth and more severe climate change impacts, resulting in higher PV of costs and PV of GHG emissions. These increased values of the objective function values are generally due the selection of a larger number of augmentation options or their implementation at an earlier stage in the planning horizon. Consequently, by using scenarios that represent a wide range of plausible future conditions, a diverse portfolio of optimal sequence plans is obtained, each representing different trade-offs between the objectives and different abilities to provide water supply security under a variety of future conditions.

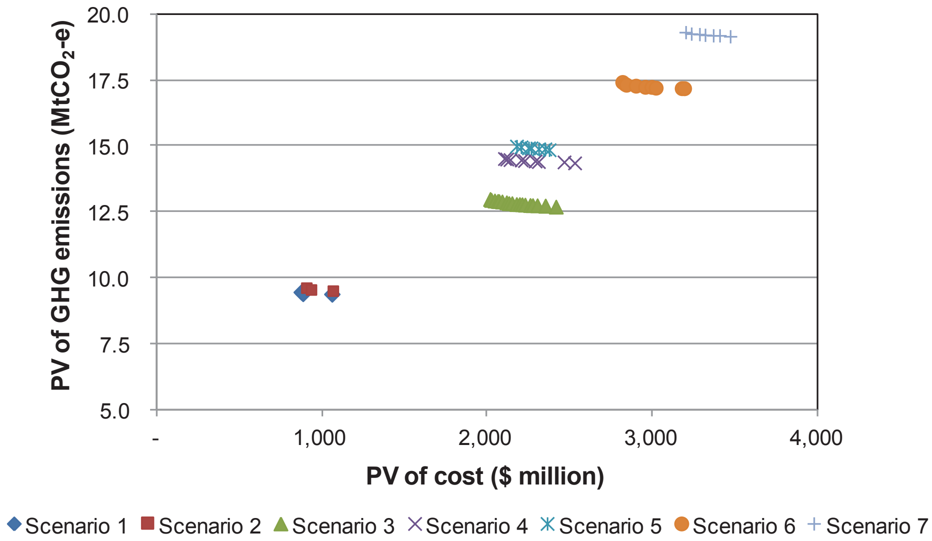

Figure 4.4 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2010-2050)

4.4.1.2 Assessment of performance of portfolio of optimal sequence plans (2010)

The Pareto-optimal solutions in Figure 4.4 contain six unique solutions at the current staging interval (2010-2020), resulting in six groups of optimal sequence plans, as shown in Table 4.4. As can be seen, one solution consists of no augmentation of the existing water supply, while the other 5 options consist of different combinations of stormwater harvesting schemes.

Table 4.4 Unique solutions at the current staging interval (2010-2020) for decision stage 1.

	Decision stage at which to implement water supply options for t = 2010 (1 = implemented at t=2010)								
Group	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_1$									
$\tilde{P}_2$									1
$\tilde{P}_3$						1			
$\tilde{P}_4$							1		
$\tilde{P}_5$						1			1
$\tilde{P}_6$							1		1

The results of the performance assessment of the six groups of optimal sequence plans are given in Figure 4.5. As can be seen, there is significant variation in PV of cost and PV of GHG emissions when the optimal sequence plans that are part of a particular group are exposed to the conditions represented by all scenarios. As expected, robustness increases as the capacity of the augmentation options increases. For example, group 1 does not have any supply augmentation and therefore has the lowest robustness, groups 2 to 4 include the addition of a single stormwater harvesting scheme, resulting in increases in robustness and groups 5 and 6 include the addition of two stormwater harvesting schemes, resulting in maximum levels of robustness. As can be seen, the flexibility of the augmentation options in Table 4.4 is highly variable, with some solutions part of optimal sequences for all seven scenarios, while others are only part of optimal sequence plans for two of the seven scenarios.

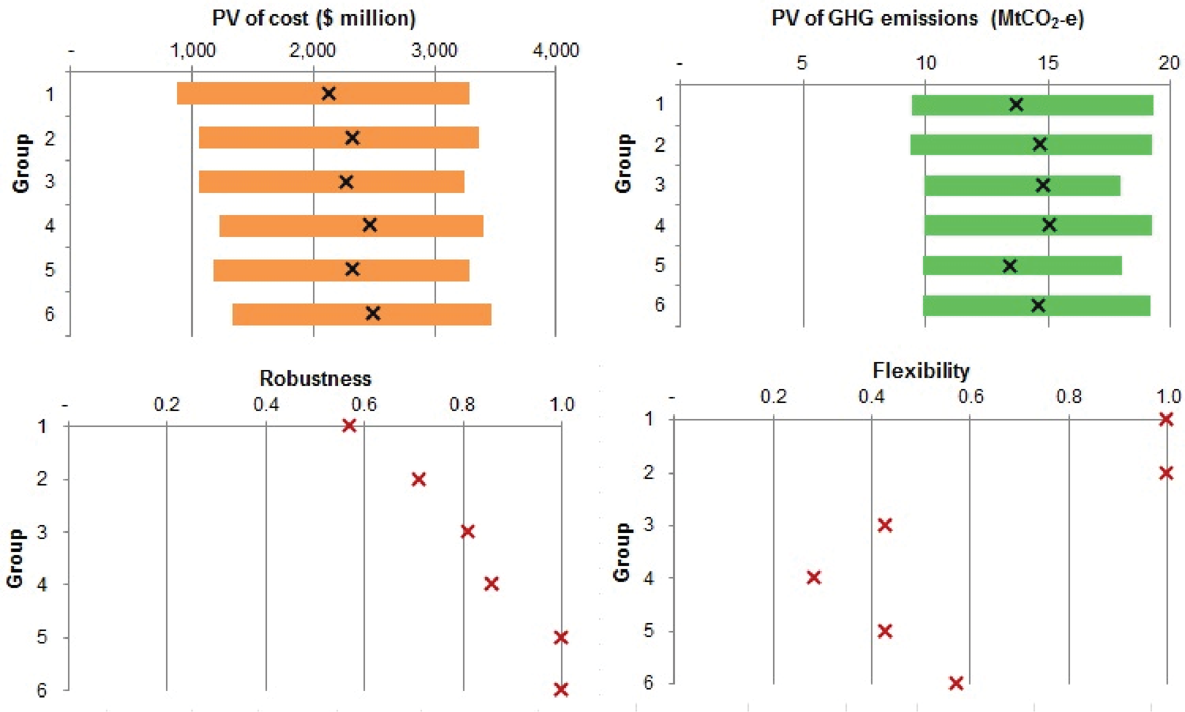

Figure 4.5 Results of performance assessment for groups with the same solution at 2010

4.4.1.3 Selection of water supply augmentation option(s) to be implemented (2010)

The value path plot corresponding to the results in Figure 4.5 is given in Figure 4.6. As can be seen, although the optimal sequence plans in groups 1 ($\tilde{P}_1$) and 2 ($\tilde{P}_2$) perform very well in terms of the median of PV of cost and flexibility, they perform poorly across the other criteria, with clearly the worst performance in terms of the range of the PV of cost, the range of the PV of GHG emissions and robustness. The optimal sequence plans in groups 4 ($\tilde{P}_4$) and 6 ($\tilde{P}_6$) have high levels of robustness, but this comes at the expense of high median PV of cost. Although these solutions perform well in terms of the range of PV of cost, they perform poorly in terms of the median and range of PV of GHG emissions and relatively poorly in terms of flexibility. The optimal sequence plans in groups 3 ($\tilde{P}_3$) and 5 ($\tilde{P}_5$) tend to perform well across all performance criteria. They clearly outperform all other groups in terms of the median and range of the PV of GHG emissions, and perform well in terms of robustness and median and range of PV of cost. Their performance in terms of flexibility is at the lower end of the spectrum, but the plans that perform best in terms of flexibility tend to perform worst in terms of robustness.

As discussed previously, the selection of which option to implement at the current decision stage depends on the priorities of the stakeholders involved. In the absence of such stakeholder input, for the purposes of illustrating the proposed approach in this paper, the sequence plans belonging to Group 3 are selected as they provide good trade-offs between the performance criteria. Consequently, the

Brownhill and Keswick stormwater harvesting scheme is chosen to be implemented at the first decision stage and fixed for the subsequent decision stages (see Table 4.4).

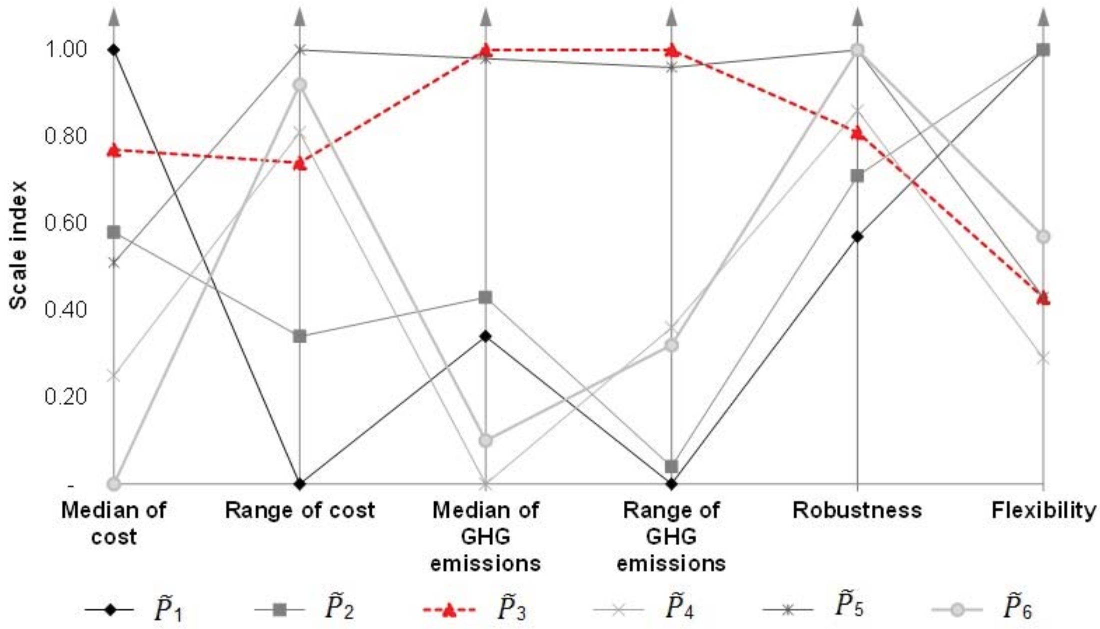

Figure 4.6 Results of performance assessment for decision stage 1 (realities 1 and 2). The value path of the selected option is highlighted in red.

4.4.1.4 Selected optimal sequence plans

The optimal sequences obtained by applying the proposed approach under the two simulated realities over the entire planning horizon and their corresponding objective function values are given in Table 4.5. As mentioned previously, each of these sequences would be developed over a period of 40 years in practice, going through the process illustrated in Section. 4.4.1.1 to 4.4.1.3 for the first decision stage (see supplementary material for results for other decision stages). As can be seen, there are significant differences between the two optimal sequences as a result of the different actual and forecast populations, rainfalls and temperatures that characterise the two realities, as well as the ability of the proposed approach to adapt to these different conditions over time. This confirms that the proposed approach is successful in adapting to changing conditions.

For both simulated realities, the 50 GL desalination plant and the Brownhill & Keswick stormwater harvesting schemes are implemented. However, the desalination plant is implemented earlier for reality 2. In addition, the 50GL desalination plant expansion and the Sturt River and Pedler Creek stormwater harvesting schemes are implemented under the more severe conditions of reality 2 in order to be able to satisfy demand. As can be seen from Table 4.5, the NPV of cost of the optimal sequence plan for reality

2 is about 1.5 times that of the optimal sequence plan for reality 1, whereas the corresponding ratio of the NPV of GHG emissions is approximately 1.2.

Table 4.5 Optimal sequences for the two simulated realities considered

	Optimal sequence for Reality 1 and Optimal sequence for Reality 2										
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme	PV of cost ($ million)	PV of GHG emissions ($MtCO_2$-e)
Optimal adaptive plan for Reality 1	3	0	0	0	0	1	0	0	0	1,537.26	12.15
Optimal adaptive plan for Reality 2	2	0	5	0	0	1	3	0	3	2,262.42	14.44

4.4.2 Utility Adaptive Features of Proposed Approach

The *average* values of the reliability and vulnerability of the water supply systems corresponding to the implementation of (i) the sequences obtained using the proposed adaptive optimal sequencing approach and (ii) the fixed optimal sequence plans for each scenario under the *actual conditions* experienced as part of the two simulated realities, with the associated average PV of cost and GHG emissions are shown in Table 4.6. As can be seen, the performance of the sequences obtained using the proposed adaptive approach is very good compared with that of the static approaches. While the NPV of cost and GHG emissions of the static sequences developed for scenarios 1 (S1) and 2 (S2) are significantly less than those of the adaptive sequences, the corresponding water supply security is not acceptable, with average reliabilities of less than 100% in all but one of the five staging intervals, ranging from 62% to 85%. Similarly, the average vulnerabilities (demand shortfalls) associated with the three staging intervals for which reliability is less than 100% ranges from 11.4% to 16.4%. In contrast, the water supply security of the adaptive plan is excellent, with 100% reliability in three of the five staging intervals and average reliabilities of 92% and 98% for the other two staging intervals and corresponding demand shortfalls of only 3% and 0.5%, respectively. In order to achieve comparable (although slightly worse – see Table 4.6) levels of water supply security when static sequence plans are considered (S4), the PV of cost increases by $329.77 Million (17.4%) and the PV of GHG emissions by 1.25 MtCO2-e (9.4%). In order to achieve better water supply security than that afforded by the adaptive plans (100% reliability for all staging intervals – S6), the PV of cost increases by $982.31 Million (51.7%) and the PV of GHG emissions by 2.31 MtCO2-e (17.7%). In addition, when using the static approach, it is unclear which of the 7 sequences to implement. Consequently, these results clearly demonstrate the advantage of using the proposed adaptive approach, compared with the corresponding static approach.

Table 4.6 Average performance of systems corresponding to the implementation of different optimal sequence plans for realities 1 and 2

	PV of cost ($ million)	PV of GHG emissions ($MtCO_2$-e)	2010 - 2020 Reliability (%)	2010 - 2020 Vulnerability (%)	2020 - 2030 Reliability (%)	2020 - 2030 Vulnerability (%)	2030 - 2040 Reliability (%)	2030 - 2040 Vulnerability (%)	2040 - 2050 Reliability (%)	2040 - 2050 Vulnerability (%)	2050 - 2060 Reliability (%)	2050 - 2060 Vulnerability (%)
Optimal fixed plan (Scenario 1)	900.10	9.74	100	0.0	85	11.4	75	13.25	62	16.4	68	14.15
Optimal fixed plan (Scenario 2)	954.95	9.92	100	0.0	85	11.4	75	13.25	62	16.4	68	14.15
Optimal adaptive plan	1899.84	13.30	100	0.0	98	0.5	100	0.0	92	3.0	100	0.0
Optimal fixed plan (Scenario 3)	2228.51	13.57	100	0.0	100	0.0	100	0.0	92	2.95	83.5	6.35
Optimal fixed plan (Scenario 4)	2229.61	14.55	100	0.0	100	0.0	100	0.0	92	2.95	92	2.2
Optimal fixed plan (Scenario 5)	2254.22	14.60	100	0.0	100	0.0	100	0.0	92	2.95	92	2.2
Optimal fixed plan (Scenario 6)	2882.15	15.66	100	0.0	100	0.0	100	0.0	100	0.0	100	0.0
Optimal fixed plan (Scenario 7)	3187.10	16.59	100	0.0	100	0.0	100	0.0	100	0.0	100	0.0

4.5 Summary and conclusions

In this paper, an adaptive, multi-objective optimal sequencing approach for urban water supply augmentation under deep uncertainty is introduced. As part of the approach, a diverse portfolio of optimal sequence plans is developed for different transient future scenarios using multi-objective evolutionary algorithms. Next, the robustness and flexibility of the components of the optimal sequence plans that have to be fixed at the current staging interval is assessed for the time period between now and the first opportunity when further changes can be made. In addition, the variability of the objective functions over the entire planning horizon is assessed and the solution that provides the best trade-offs between these criteria, in accordance with stakeholder preferences, is selected. This process is repeated for the next decision stages, when updated information is available. In this way, the approach is able to successfully balance the need for the development of optimal longer-term plans under deep uncertainty with the need to be able to respond to changes as they arise and to provide robust solutions between decision stages. It also provides a computational method in support of the successful implementation of dynamic adaptive planning as a paradigm for dealing with deep uncertainty.

In order to demonstrate the utility of the proposed approach, it is applied to the optimal sequencing of urban water supply augmentation options for a case study based on the southern Adelaide water supply system from 2010 to 2060. In order to illustrate the impact of the adaptive nature of the approach, two different simulated realities are considered. The results indicate that the approach is successful in adapting to changing conditions, while optimising longer-term objectives and satisfying water supply security constraints along the planning horizon, in highly uncertain planning environments. This is evidenced by the differences in the optimal solutions obtained for the different realities, as well as the favourable performance of the adaptive plans compared with those fixed at the beginning of the planning horizon.

Despite the methodological advances of the proposed approach, there remain a number of avenues for future improvement. Firstly, as mentioned previously, informal approaches to scenario development and the determination of which solution to implement are used. Consequently, the value of using more formal approaches for these steps should be explored, especially for more complex problems and for real-life applications. Secondly, the problem formulation (e.g. objectives, constraints, decision variables) is assumed to remain constant throughout the planning horizon, which is unlikely to be the case. Consequently, the incorporation of approaches that enable the problem formulation to be changed over time should be explored (see Maier et al., 2014). Thirdly, as discussed in Section 4.2.5, based on the philosophical approach that underpins the proposed method, the solutions obtained might not be mathematically optimal. It would be interesting to assess the impact of this in future studies by comparing the results obtained using the proposed approach with that of Kang and Lansey (2014), for example. Finally, although the approach was presented and applied in the context of urban water supply augmentation, it is also applicable to a number of other water resources scheduling and sequencing problems, as mentioned previously. Consequently, it would be useful to tailor and apply the approach presented in this paper to other problem domains.

4.6 Acknowledgements

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4.7 Supplementary material

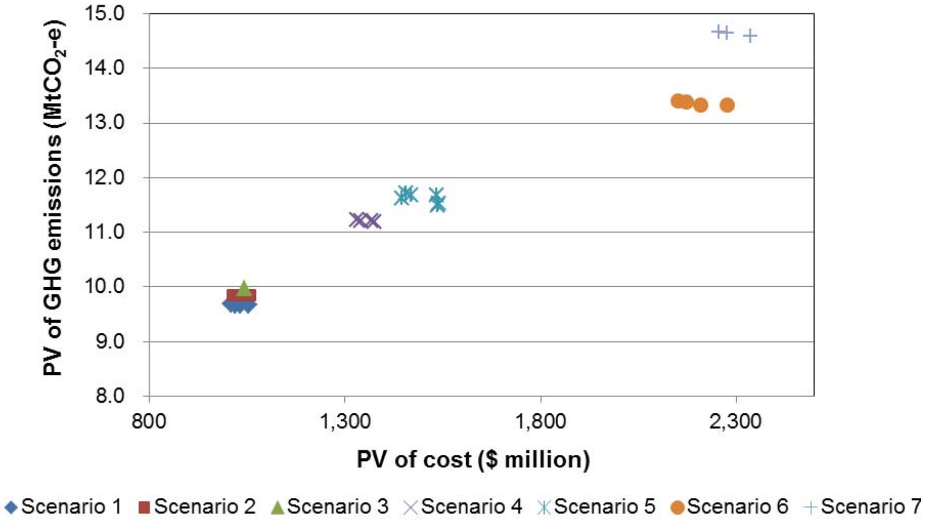

Figure 4.7 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2020-2060)(reality 1)

Table 4.7 Unique solutions at the current staging interval (2020-2030) for decision stage 2 (reality 1)

Group	Decision stage at which to implement water supply options for t = 2020 (1 = implemented at t=2010, 2 = implemented at t=2020)								
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_{1,R1}$						1			
$\tilde{P}_{2,R1}$						1			2
$\tilde{P}_{3,R1}$						1		2	2
$\tilde{P}_{4,R1}$						1		2	

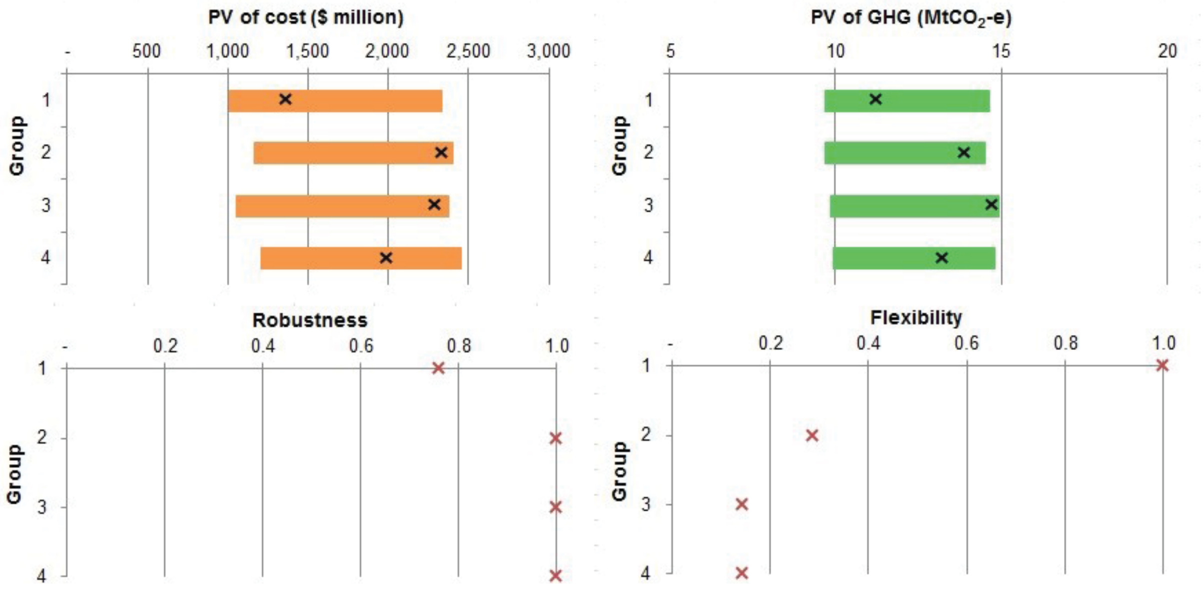

Figure 4.8 Results of performance assessment for groups with the same solution for decision stage 2 (reality 1)

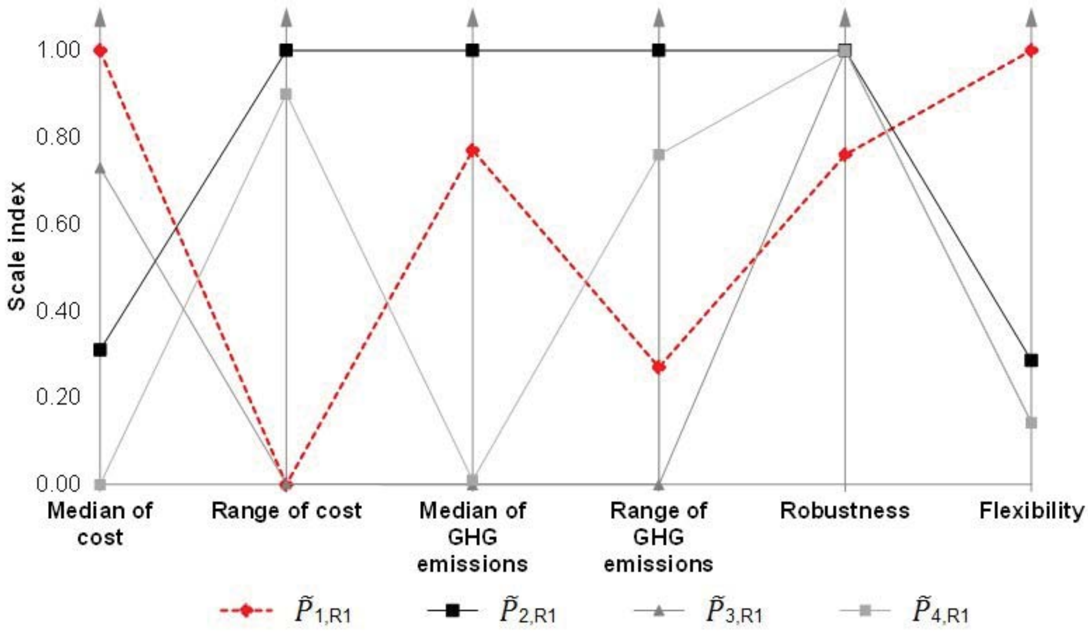

Figure 4.9 Results of performance assessment for decision stage 2 (realities 1)

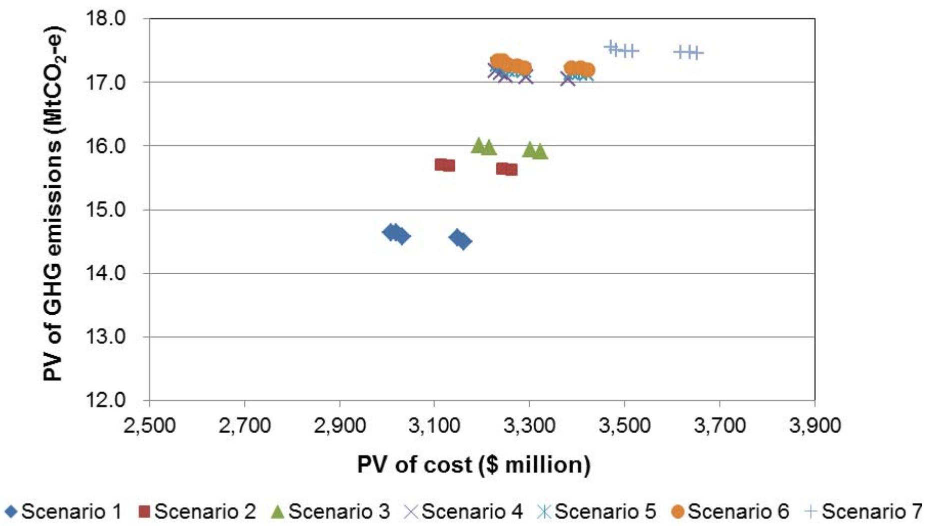

Figure 4.10 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2020-2060) (reality 2)

Table 4.8 Unique solutions at the current staging interval (2020-2030) for decision stage 2 (reality 2)

Group	Decision stage at which to implement water supply options for t = 2020 (1 = implemented at t=2010, 2 = implemented at t=2020)								
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_{1,R2}$	2					1			
$\tilde{P}_{2,R2}$	2					1			2

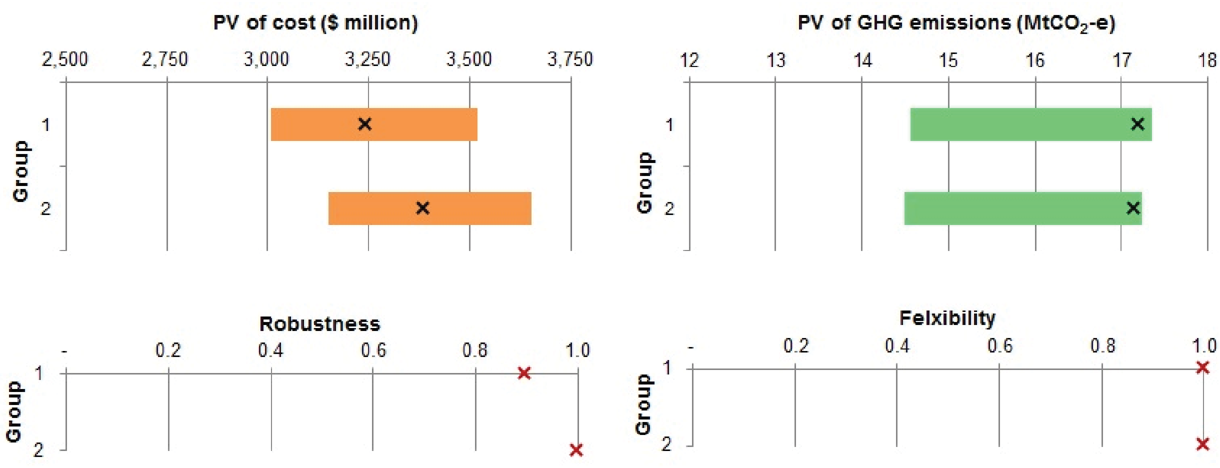

Figure 4.11 Results of performance assessment for groups with the same solution for decision stage 2 (reality 2)

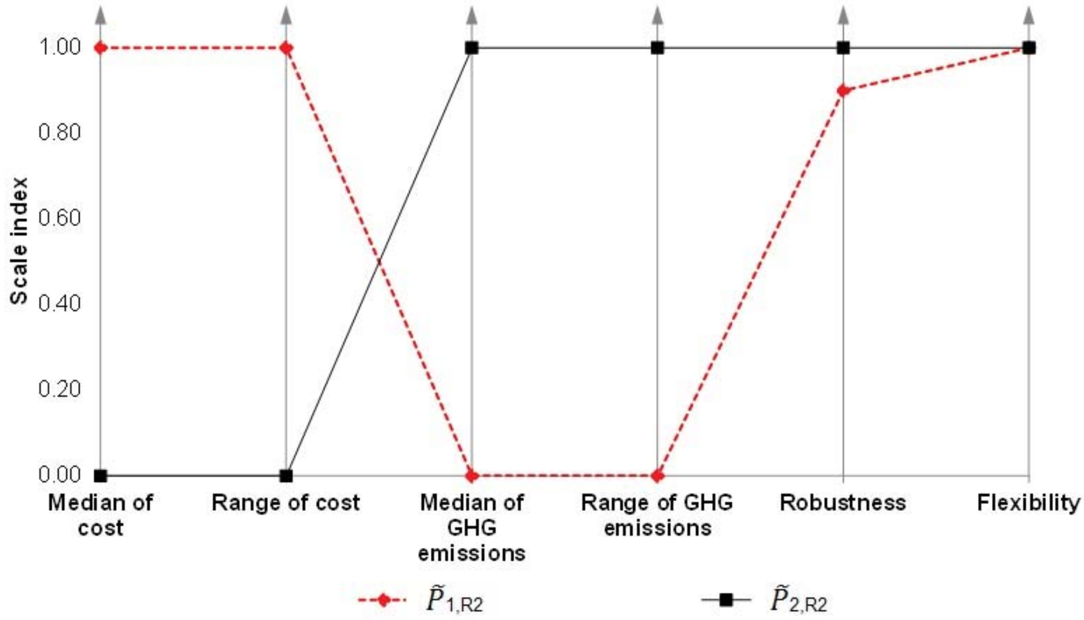

Figure 4.12 Results of performance assessment for decision stage 2 (realities 2)

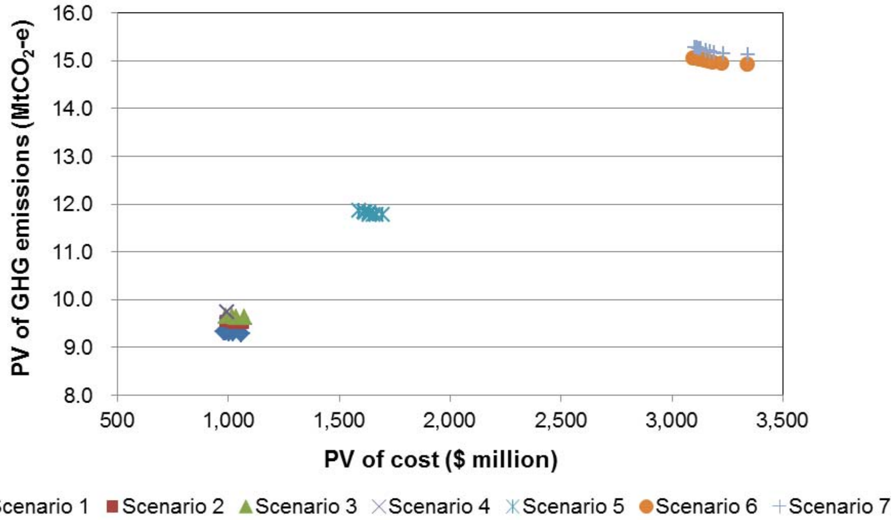

Figure 4.13 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2030-2070) (reality 1)

Table 4.9 Unique solutions at the current staging interval (2030-2040) for decision stage 3 (reality 1)

Group	Decision stage at which to implement water supply options for t = 2030 (1 = implemented at t=2010, 2 = implemented at t=2020, 3 = implemented at t=2030)								
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_{1,R1}$						1			3
$\tilde{P}_{2,R1}$	3					1			
$\tilde{P}_{3,R1}$	3					1			3

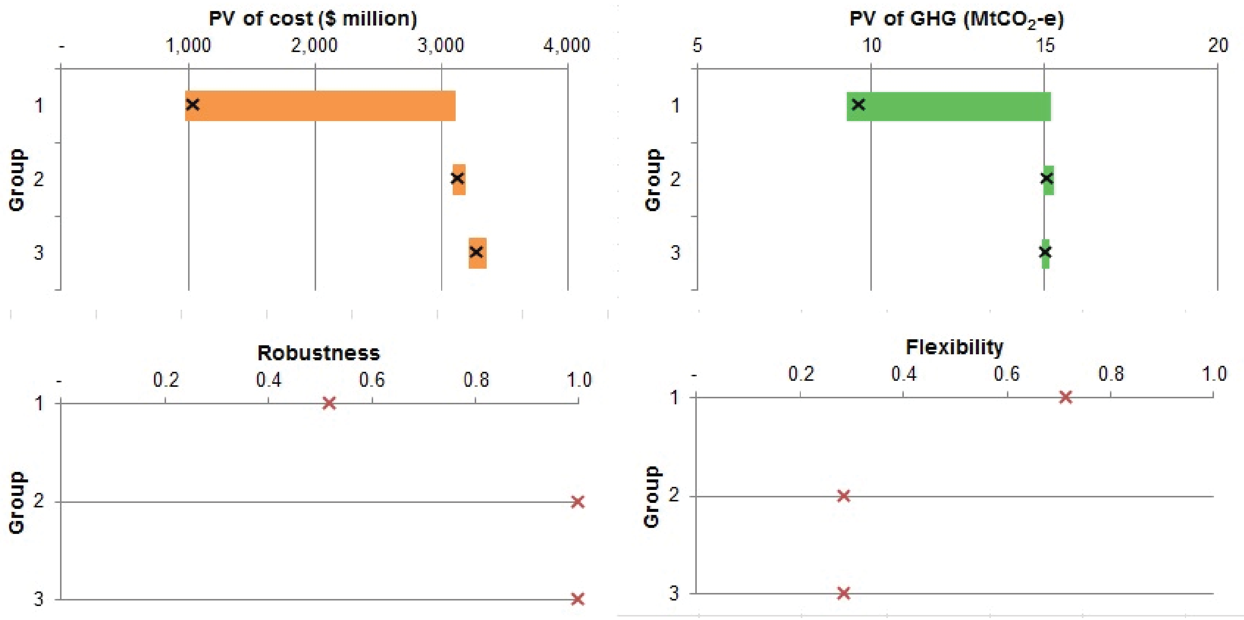

Figure 4.14 Results of performance assessment for groups with the same solution for decision stage 3 (reality 1)

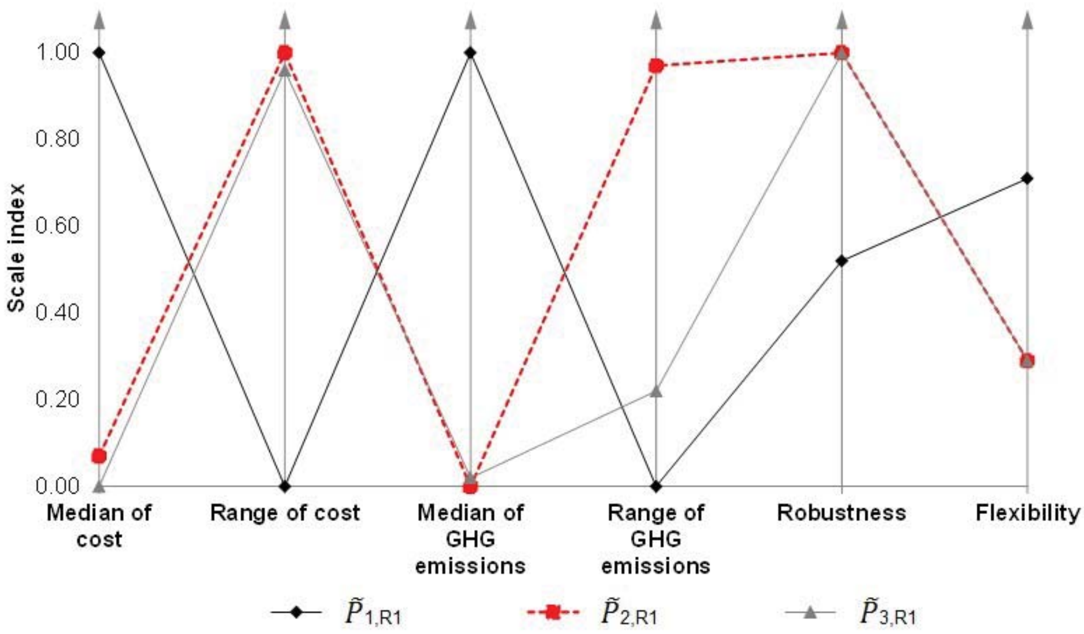

Figure 4.15 Results of performance assessment for decision stage 3 (realities 1)

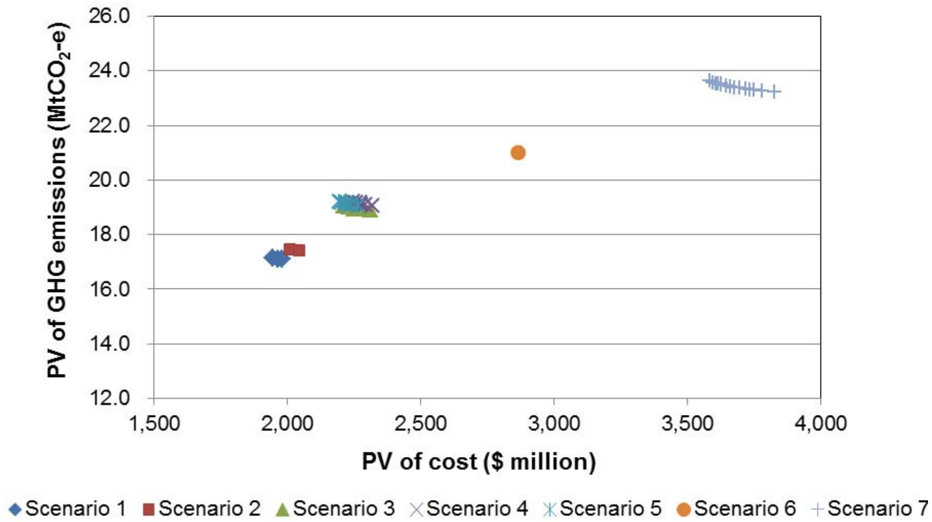

Figure 4.16 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2030-2070) (reality 2)

Table 4.10 Unique solutions at the current staging interval (2030-2040) for decision stage 3 (reality 2)

Group	Decision stage at which to implement water supply options for t = 2030 (1 = implemented at t=2010, 2 = implemented at t=2020, 3 = implemented at t=2030)								
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_{1,R2}$	2					1			
$\tilde{P}_{2,R2}$	2					1			3
$\tilde{P}_{3,R2}$	2					1	3		3

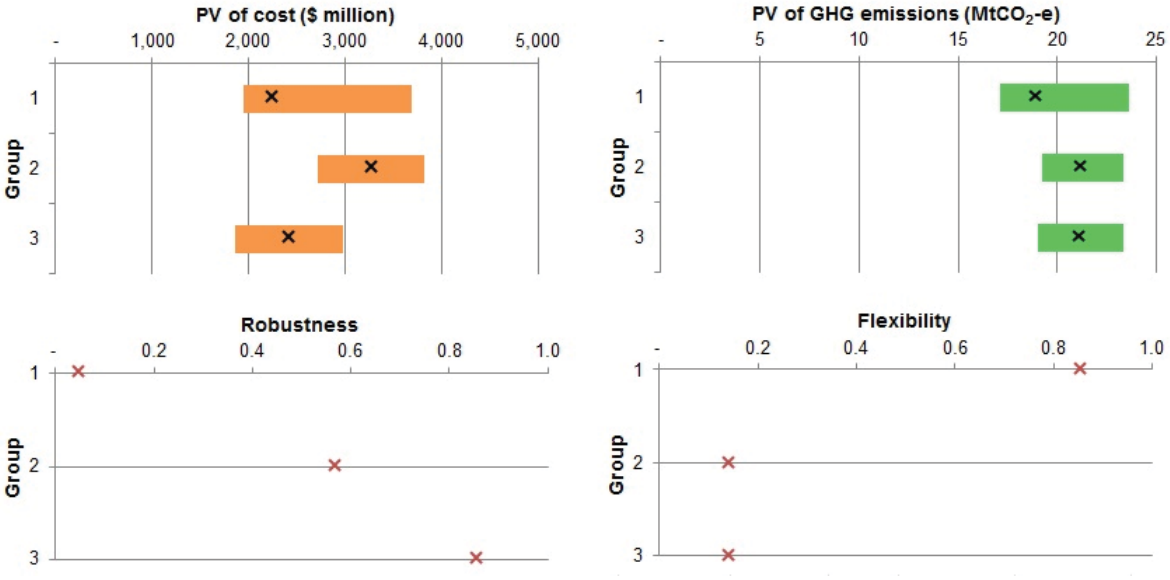

Figure 4.17 Results of performance assessment for groups with the same solution for decision stage 3 (reality 2)

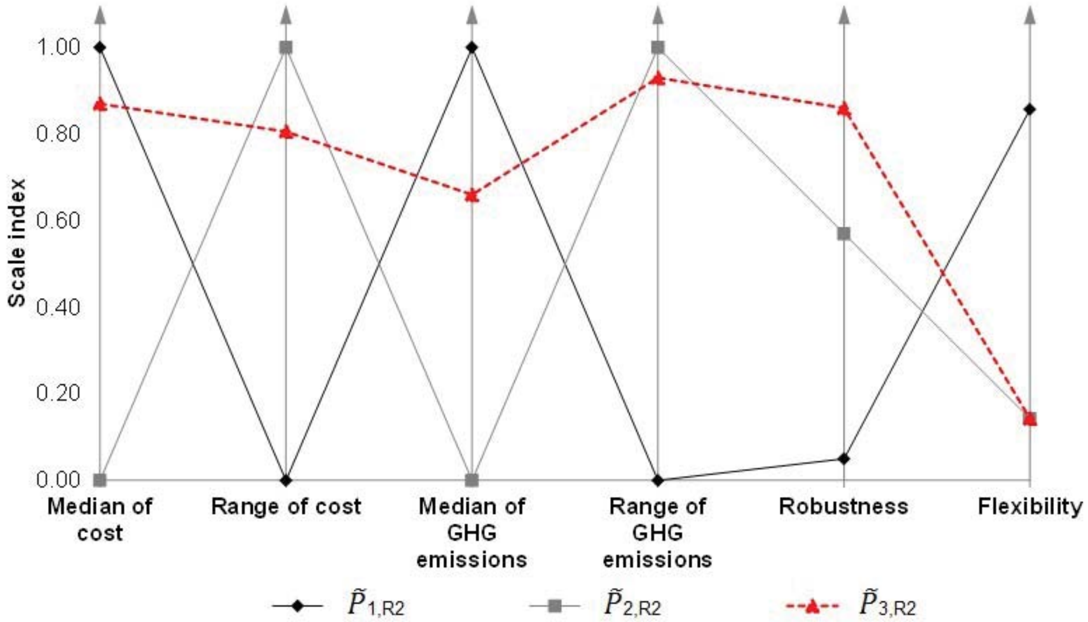

Figure 4.18 Results of performance assessment for decision stage 3 (realities 2)

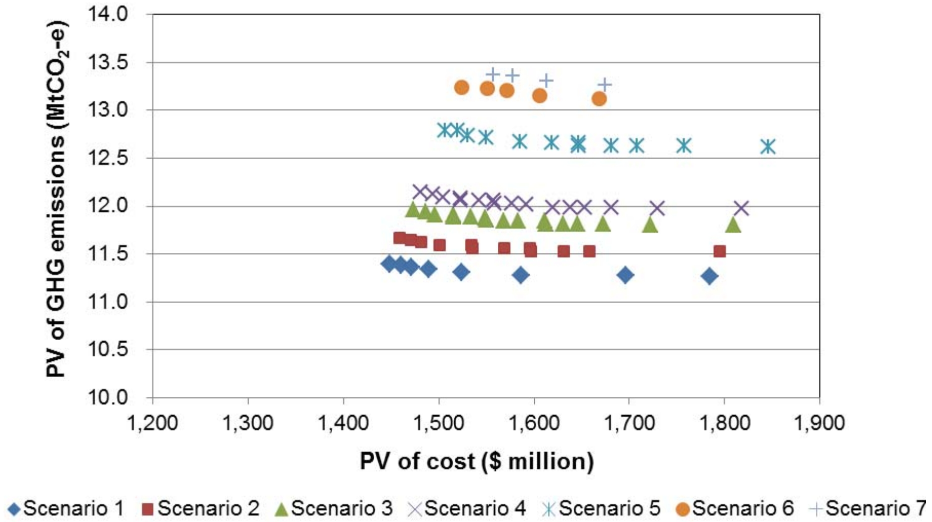

Figure 4.19 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2040-2080) (reality 1)

Table 4.11 Unique solutions at the current staging interval (2040-2050) for decision stage 4 (reality 1).

Group	Decision stage at which to implement water supply options for t = 2040 (1 = implemented at t=2010, 2 = implemented at t=2020, …, 4 = implemented at t=2040)								
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_{1,R1}$	3					1			
$\tilde{P}_{2,R1}$	3					1			4
$\tilde{P}_{3,R1}$	3					1	4		4

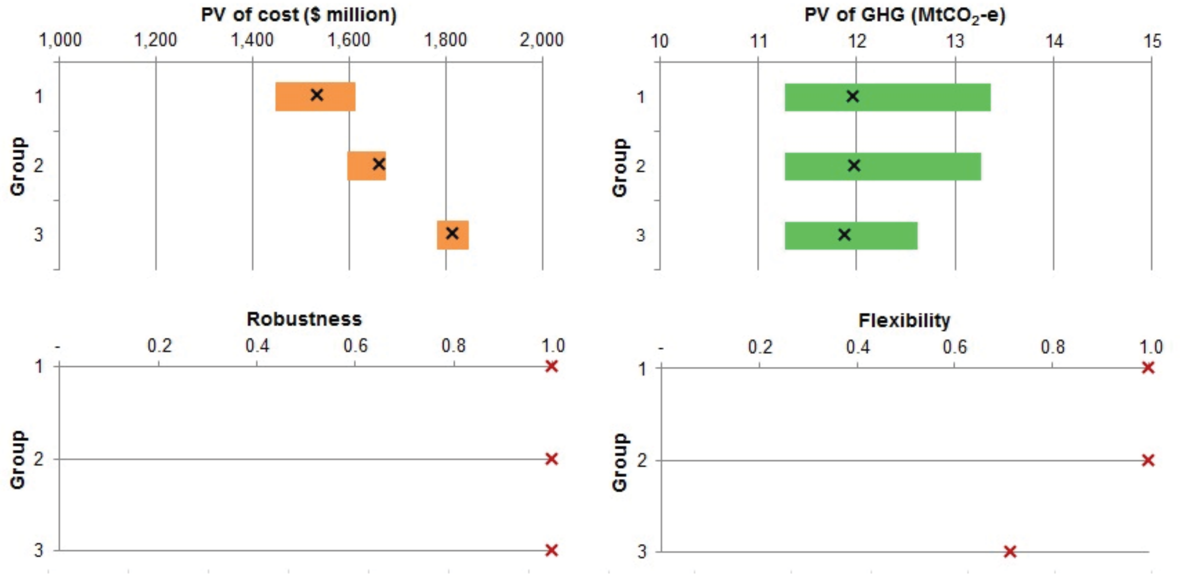

Figure 4.20 Results of performance assessment for groups with the same solution for decision stage 4 (reality 1)

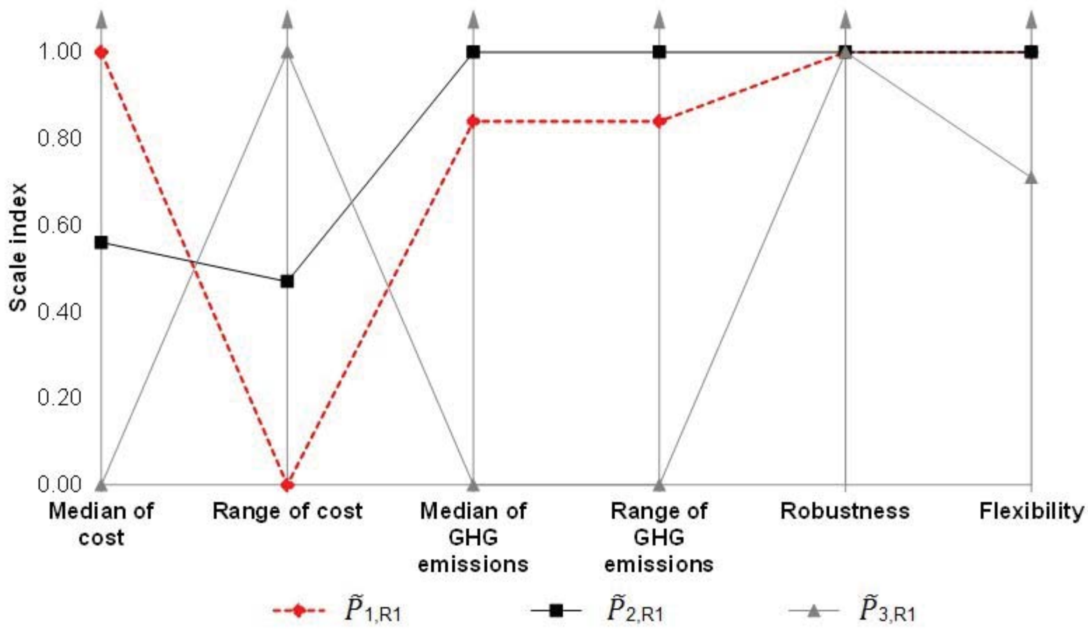

Figure 4.21 Results of performance assessment for decision stage 4 (realities 1)

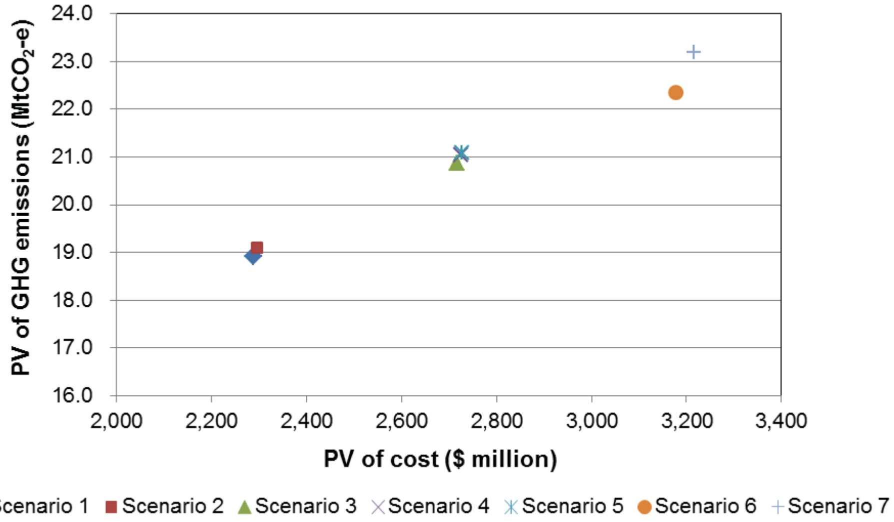

Figure 4.22 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2040-2080) (reality 2)

Table 4.12 Unique solutions at the current staging interval (2040-2050) for decision stage 4 (reality 2).

Group	Decision stage at which to implement water supply options for t = 2040 (1 = implemented at t=2010, 2 = implemented at t=2020, …, 4 = implemented at t=2040)								
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_{1,R2}$	2					1	3		3

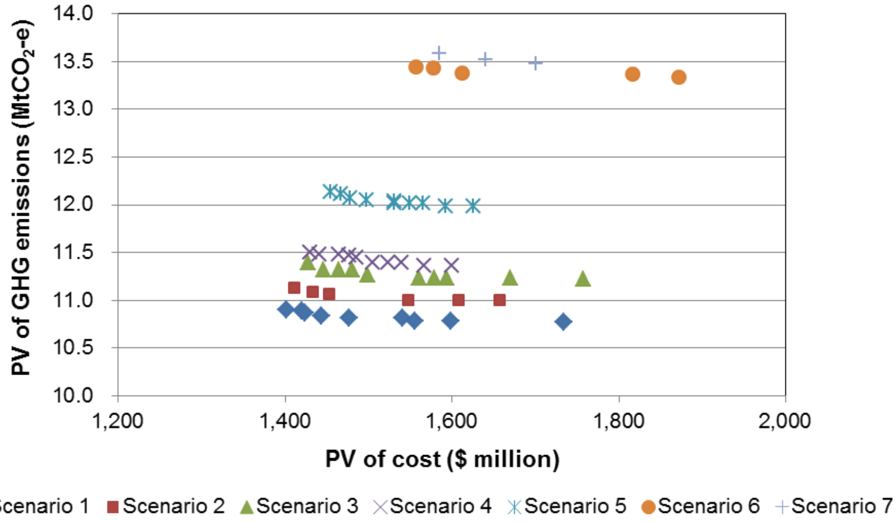

Figure 4.23 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2050-2090) (reality 1)

Table 4.13 Unique solutions at the current staging interval (2050-2060) for decision stage 5 (reality 1).

Group	Decision stage at which to implement water supply options for t = 2050 (1 = implemented at t=2010, 2 = implemented at t=2020, …, 5 = implemented at t=2050)								
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_{1,R1}$	3					1			
$\tilde{P}_{2,R1}$	3					1			5
$\tilde{P}_{3,R1}$	3					1	5		
$\tilde{P}_{4,R1}$	3					1	5		5

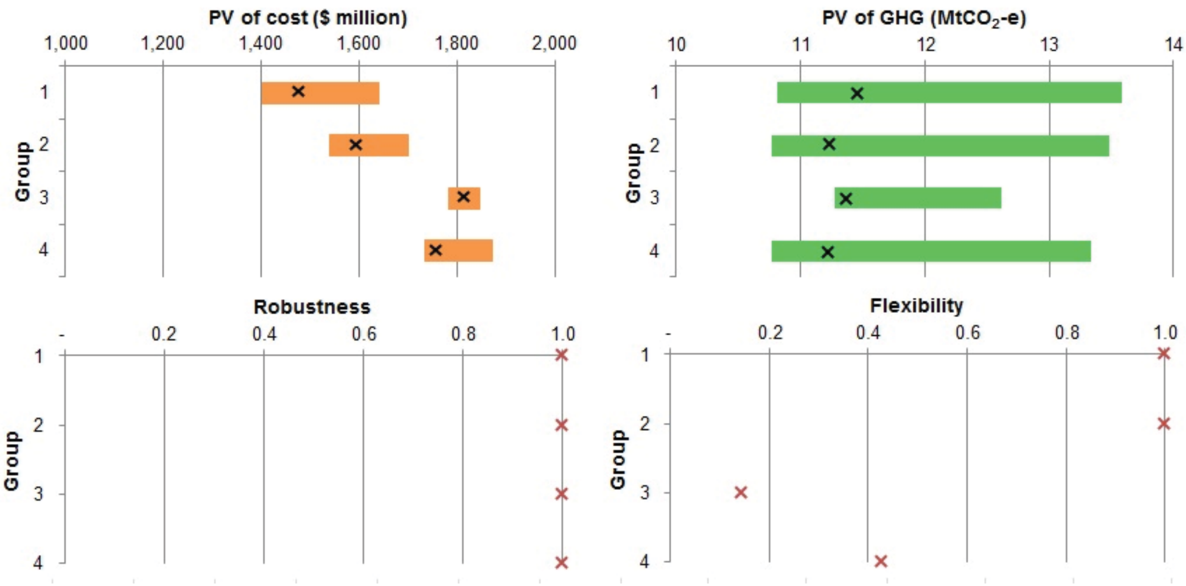

Figure 4.24 Results of performance assessment for groups with the same solution for decision stage 5 (reality 1)

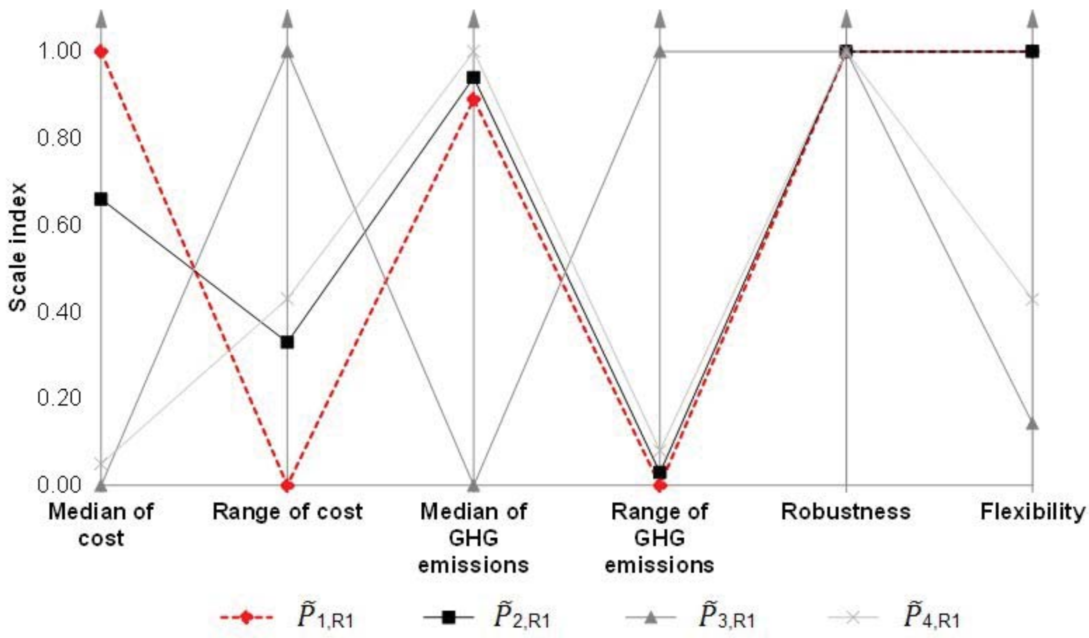

Figure 4.25 Results of performance assessment for decision stage 5 (realities 1)

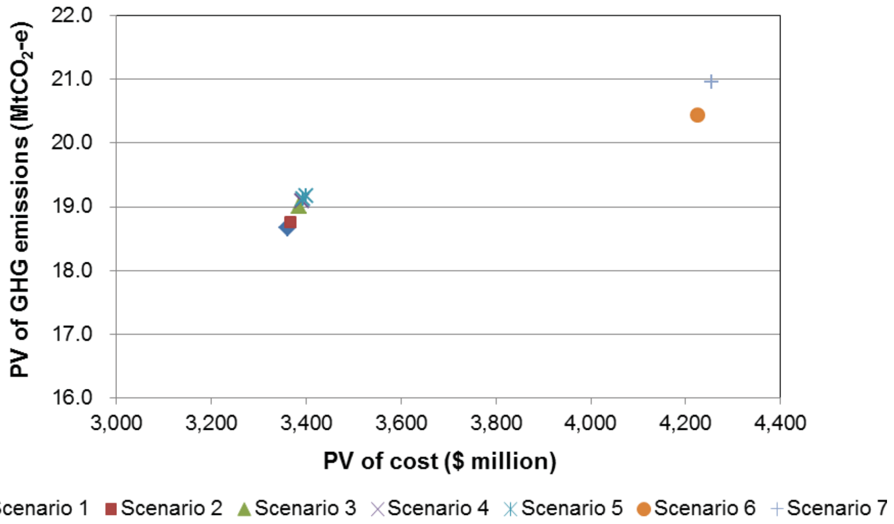

Figure 4.26 Tradeoff between the PV of GHG emissions and the PV of cost for the seven projected possible future scenarios (2050-2090) (reality 2)

Table 4.14 Unique solutions at the current staging interval (2050-2060) for decision stage 5 (reality 2)

Group	Decision stage at which to implement water supply options for t = 2050 (1 = implemented at t=2010, 2 = implemented at t=2020, …, 5 = implemented at t=2050)								
	50GL desalination plant	100GL desalination plant	50GL desalination expansion	Rainwater tank	Tank size	Brownhill & Keswick Creek stormwater harvesting scheme	Sturt River stormwater harvesting scheme	Field River stormwater harvesting scheme	Pedler Creek stormwater harvesting scheme
$\tilde{P}_{1,R2}$	2		5			1	3		3

Chapter 5

5 Thesis Summary

Sequencing of water supply sources involves selecting the supply sources to implement at specific stages over a planning horizon. This approach has long been used to identify water supply sources that maintain water supply security. However, in recent years, the sequencing of urban water supply sources has been complicated by a number of factors, including the consideration of alternative sources of water (e.g. desalination, stormwater, rainwater, recycled wastewater), the inclusion of multiple sustainability criteria (e.g. economic, environmental, social) and the consideration of extended planning period (e.g. 50 to 100 years). A review of the sequencing of urban water supply sources studies showed that traditional sequencing approaches have generally not considered the following: (i) multiple sustainability criteria; (ii) various water supply sources in a regional water supply system; (iii) extended planning horizons; (iv) uncertainties associated with the extended planning horizons; and (v) robustness/ adaptation in solutions to cope with changes in the system over an extended planning period. Thus, advanced sequencing approaches are developed to address the knowledge gaps revealed from the literature. The proposed approaches have been applied to the case study of the southern Adelaide water supply system to demonstrate their effectiveness and their ability to provide useful information for managers of the system.

5.1 Research Contributions

The overall contribution of this thesis is the development of robust, adaptive, multi-objective optimal sequencing approaches for an urban water system with various supply sources under deep uncertainty. The proposed approaches enable optimal sequence plans to be generated in order to minimise economic and environmental costs, and deep uncertainty to be considered with the aid of robustness and adaptation. The utility of the approaches is demonstrated using a real case study with information gained being able to assist with the decision making process related to the future planning and management of Adelaide’s water supply sources.

Specifically, in meeting the objectives of this research mentioned in the introduction (Chapter 1), the following research contributions were made:

1. In the first paper, the two approximate optimal sequencing approaches, the “build up” (BU) and “build to target” (BTT) methods are developed to incorporate multiple objectives into the

sequencing of alternative water supply sources at the regional scale. The approaches consider various water supply options, such as traditional surface water resources and desalination, as well as stormwater and rainwater harvesting. In addition, the impact of different objective function weightings and sequencing approaches on (i) the optimal sequences of alternative water supply sources; and (ii) the objective function values, is assessed under a range of possible scenarios for the case study. The results obtained show that the BU method generally results in less favourable objective function values, but is more flexible and responsive to future changes compared with the BTT method.

2. In the second paper, the sequencing approach is enhanced by utilising multi-objective evolutionary algorithms (Water System Multi-objective Genetic Algorithm), coupled with a water supply system simulation model (i.e. *WaterCress*), to identify a diverse portfolio of optimal sequences by obtaining optimal sequences under deep uncertainty and selecting optimal sequences that are diverse in terms of solutions and trade-offs between objectives. Then, global sensitivity analysis using Sobol' 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. 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 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.

3. In paper 3, the approach presented in paper 2 is extended by adding adaptive capacity. As part of the approach, a diverse portfolio of optimal sequence plans is developed for different future scenarios using multi-objective evolutionary algorithms. Next, the robustness and flexibility of the components of the optimal sequence plans that have to be "locked in" at the current staging interval is assessed for the time period between now and when further changes can be made. In addition, the variability of the objective functions over the entire planning horizon is assessed and the solution that provides the best trade-offs between these criteria is selected. This process is repeated for the next decision stages, when updated information will be available. In this way, the approach is able to successfully balance the need for the development of optimum longer-term plans with the need to be able to respond to changes as they arise. The results

indicate that the approach is successful in adapting to changing conditions, while optimising longer-term objectives and satisfying water supply security constraints along the planning horizon, in highly uncertain planning environments. This was shown by the differences in the optimal solutions obtained for the different realities, as well as the favourable performance of the adaptive plans when compared to those fixed at the beginning of the planning horizon, even if future conditions were known with reasonable certainty.

5.2 Research Limitations

The limitations of this research are discussed below.

1. As part of the case study, the problem formulation (e.g. objectives, constraints, decision variables) is assumed to remain constant throughout the planning horizon, which is unlikely to be the case. Consequently, the incorporation of approaches that enable the problem formulation to be changed over time should be explored.

2. System reliability is considered as a constraint to be satisfied at each decision stage. However, there might be advantages in including reliability as an objective, as this enables trade-offs between reliability and other objectives to be explored explicitly. In addition, the use of other risk-based system performance measures that not only take account of the probability of system failure (i.e. demand exceeding supply capacity), but also the consequences of system failure, are an important consideration.

3. As part of the case study, informal approaches to scenario development and the determination of the solutions that represent the “best” trade-offs between performance criteria are used. The value of using more formal approaches for these steps should be explored, especially for more complex problems and for real-life applications.

4. 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 large range of future conditions, and the development of flexible solutions, which are designed to enable adaptation to changing future conditions. One of the limitations is that robustness and flexibility are calculated post-optimisation, thereby only enabling the robustness and flexibility of solutions that are optimal with respect to the objectives to be assessed, rather than optimising robustness

and flexibility explicitly. Consequently, robustness and/or flexibility should be considered as objectives during the optimisation process.

5.3 Recommendations for Future Work

This research has introduced new approaches to the sequencing of urban water supply sources in a robust and adaptive manner. However, there are still opportunities to address the limitations identified above as part of future studies:

1. Considering the changes of the formulation of the optimisation problem over time. For example, values of the future uncertain variables (e.g. demand, discount rate, energy cost and etc.) could be re-estimated at a regular time-step. Possible changes in objectives and/or constraints during the planning horizon should also be considered.

2. Incorporating robustness and/or flexibility as objectives during the optimisation process, rather than calculating them post-optimisation. This would enable robustness and adaptability to be considered as objectives in the optimisation process explicitly.

3. Using more formal approaches, such as scenario discovery (e.g. Lempert and Groves, 2010, Kasprzyk et al., 2013b) and multi-criteria decision analysis (Korteling et al., 2013, Hyde and Maier, 2006) for scenario development and the selection of the “final” optimal sequence plans could be investigated in future research, especially for more complex problems.

4. Altering the scope of the model to incorporate wastewater reuse schemes, agricultural demands, water sensitive urban design and cluster or unit scale modelling. Furthermore, other sustainability indicators (e.g. social benefits) could be investigated to provide different trade-offs.

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Appendix A

Copy of Paper from Chapter 2

BEH, E. H. Y., DANDY, G. C., MAIER, H. R. & PATON, F. L. 2014. Optimal sequencing of water supply options at the regional scale incorporating alternative water supply sources and multiple objectives. Environmental Modelling & Software 53 137-153.

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Appendix B

Copy of Paper from Chapter 3

BEH, E. H. Y., MAIER, H. R. & DANDY, G. C. 2015. Scenario Driven Optimal Sequencing under Deep Uncertainty, *Environmental Modelling and Software*, 68, 181-195, DOI:10.1016/j.envsoft.2015.02.006.

Beh, E.H.Y., Maier, H.R. & Dandy, G.C. (2015). Scenario Driven Optimal Sequencing under Deep Uncertainty.
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Appendix C

Copy of Paper from Chapter 4

BEH, E. H. Y., MAIER, H. R. & DANDY, G. C. 2015. Adaptive, Multiobjective Optimal Sequencing Approach for Urban Water Supply Augmentation under Deep Uncertainty, Water Resour. Res., 51, DOI:10.1002/ 2014WR016254.

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Water Resources Research

RESEARCH ARTICLE

10.1002/2014WR016254

Key Points:

- Multiobjective optimal sequencing under deep uncertainty
- Consideration of robustness, flexibility, and adaptation
- Application to case study based on the southern Adelaide water supply system

Supporting Information:

- Supplementary Material

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Adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty

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Abstract Optimal long-term sequencing and scheduling play an important role in many water resources problems. The optimal sequencing of urban water supply augmentation options is one example of this. In this paper, an adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty is introduced. As part of the approach, optimal long-term sequence plans are updated at regular intervals and trade-offs between the robustness and flexibility of the solutions that have to be fixed at the current time and objectives over the entire planning horizon are considered when selecting the most appropriate course of action. The approach is demonstrated for the sequencing of urban water supply augmentation options for the southern Adelaide water supply system for two assumed future realities. The results demonstrate the utility of the proposed approach, as it is able to identify optimal sequences that perform better than those obtained using static approaches.

1. Introduction

Formal optimization methods for sequencing or scheduling play an important role in *long-term* management and planning for a number of water resources problems, such as the sequencing of urban water supply augmentation options [*Beh et al.*, 2014; *Mortazavi-Naeini et al.*, 2014; *Ray et al.*, 2012], the sequencing of urban water supply infrastructure [*Kang and Lansey*, 2014], scheduling the replacement of urban water supply mains [*Dandy and Engelhardt*, 2001, 2006], investment scheduling for irrigated agricultural expansion planning [*Allam and Marks*, 1984], management of water supply systems [*Housh et al.*, 2013], and the scheduling of environmental flows in rivers [*Szemis et al.*, 2012, 2013]. The focus of this paper is on urban water supply augmentation, for which the optimal sequencing of supply sources has long been used to identify systems that maintain water supply security and minimize water supply costs [e.g., *Becker and Yeh*, 1974; *Butcher et al.*, 1969; *Morin and Esogbue*, 1971; *Atkinson*, 2002]. As part of the optimal sequencing process, the best combination of supply augmentation options that is able to satisfy projected demands over a long-term planning period (e.g., 30–50 years) is identified. The optimal sequencing of these options over the planning period is also determined, in recognition of the fact that demands are likely to change over time. Consequently, decisions in relation to which augmentation options should be implemented are made at a number of decision points over the planning horizon, which are generally spaced at regular time intervals (e.g., 10 years), resulting in a number of staging intervals over the planning horizon.

In the past, optimal sequencing approaches have considered traditional sources of water, such as reservoirs and groundwater, and have attempted to minimize cost objectives [e.g., *Chang et al.*, 2009; *Connarty and Dandy*, 1996]. More recently, multiple objectives [e.g., *Beh et al.*, 2012, 2014; *Mortazavi-Naeini et al.*, 2014] and alternative sources of water, such as desalinated water, storm water, rainwater, and reclaimed wastewater [e.g., *Beh et al.*, 2012, 2014; *Downs et al.*, 2000; *Ray et al.*, 2012] have been considered. However, while uncertainties about future conditions, such as population growth, per capita demand and hydrological inputs, have been considered in the determination of optimal portfolios of future urban water supply and demand management options [e.g., *Kasprzyk et al.*, 2009, 2012, 2013; *Paton et al.*, 2014b; *Zeff et al.*, 2014], they have generally not been considered in the optimal *sequencing* of these options. In other words, while these uncertainties have been considered in determining *which* sources are best suited to satisfying demand at some time in the future, they have not been considered in relation to the *timing* of the implementation of these sources over the planning horizon, which is a much more complex problem. Only *Ray et al.* [2012] have developed a formal optimization approach for the sequencing of long-term urban water supply augmentation options under deep uncertainty, which is uncertainty associated with multiple possible futures for which relative probabilities are unknown (e.g., climate change and population growth [*Lempert et al.*, 2003]). However, it should be noted that the approaches of *Housh et al.* [2013] and *Kang and Lansey* [2014] could also be used for this purpose, even though they were developed for the optimal sequencing of urban water supply infrastructure and water supply system management options, respectively.

A potential disadvantage of the approaches of *Ray et al.* [2012] and *Housh et al.* [2013] is that they are based on what are generally referred to as traditional optimization methods (i.e., linear and stochastic programming, respectively, in this case), which have a number of shortcomings compared with evolutionary optimization approaches [see *Maier et al.*, 2014; *Mortazavi-Naeini et al.*, 2014]. Some of these shortcomings include not being able to be linked with simulation models of the urban water supply system under consideration, thereby potentially ignoring important nonlinear interactions [*Matrosov et al.*, 2013b], and not being truly multiobjective. Although *Kang and Lansey* [2014] use a genetic algorithm as their optimization engine and indicate that their approach could be extended to include multiple objectives, this was not done in their paper.

The approaches presented in *Ray et al.* [2012], *Housh et al.* [2013], and *Kang and Lansey* [2014] do not include *formal* mechanisms for updating optimal sequences over time when new information about current and plausible future conditions becomes available. Consequently, these approaches can be considered to deal with deep uncertainty by way of “static robustness,” which aims to reduce vulnerability under the largest range of plausible future conditions [*Walker et al.*, 2013]. However, given that optimal urban water supply augmentation sequence plans are generally developed over periods of 30–50 years, with augmentation options added incrementally over time (e.g., at 5 or 10 year intervals), there is likely to be significant benefit in developing an optimal sequencing approach that deals with deep uncertainty by way of “dynamic robustness,” which considers adaptation over time as conditions change [*Walker et al.*, 2013]. It should be noted that although any of the above sequencing approaches could be applied using a sliding temporal window and *Kang and Lansey* [2014] include an explicit flexibility criterion in their optimization process and mention that their approach should be reapplied periodically, these adaptive mechanisms have not been *formalized* and their utility has not been *demonstrated*. The lack of the explicit application of an adaptive approach could at least in part be due to the difficulty of being able to test the adaptive mechanisms of such sequencing approaches, as adaptation needs to respond to changes in future conditions, which have not yet occurred and are therefore unknown. Consequently, there would be value in developing an experimental approach for testing the potential benefits of formal adaptive optimization approaches compared with currently used static (i.e. non-adaptive) approaches.

Given that existing multiobjective approaches to the optimal sequencing of water supply augmentation options are deterministic [e.g., *Mortazavi-Naeini et al.*, 2014] and that existing optimal sequencing approaches that do consider uncertain future conditions are not multiobjective and do not include any *formal* mechanisms for adaptation, there is a need to develop a multiobjective, adaptive optimisation approach for the sequencing of urban water supply augmentation options. However, as pointed out by *Kwakkel et al.* [2014], the use of dynamic adaptive plans, rather than static plans, represents an emerging planning paradigm for dealing with deep uncertainty. As such, implementation of this paradigm represents a major challenge, especially in terms of the development of computational methods that support the development of such plans, including consideration of transient scenarios [*Kwakkel et al.*, 2014]. This is particularly the case for the urban water supply augmentation problem, as infrastructure decisions are difficult to reverse and have long lifespans, making it difficult to develop dynamic, adaptive pathways. In addition, because of long lead times and large investments associated with urban water supply infrastructure, there is a need to ensure that water supply security is not compromised in periods between the implementation of augmentation options.

It follows that an adaptive approach to the optimal sequencing of urban water supply augmentation options is not simply a matter of reapplying an optimal static approach over a sliding window [see *Szemis et al.*, 2014], but requires careful design so that it enables the identification of (i) augmentation sequences that are both optimal for the long term, yet sufficiently flexible to be able to be adapted with minimal loss of optimality and (ii) augmentation options that are robust to changing conditions in periods between the implementation of augmentation options. In other words, such an approach should account for (i) dynamic

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robustness over the entire planning horizon, (ii) static robustness during those periods of the planning horizon when no changes can be made to the system, and (iii) pathways that are sufficiently flexible to cater to adaptation at minimal loss of optimality.

Consequently, the objectives of this paper are (i) to develop an formal optimal sequencing approach for urban water supply augmentation that is multiobjective and adaptive and (ii) to demonstrate the application of the approach to a case study based on the southern Adelaide water supply system in South Australia, including the development of an experimental approach that enables the potential benefits of adaptive approaches to be compared with currently used static approaches. The remainder of this paper is organized as follows. The proposed optimal sequencing approach is introduced in section 2 and its application to the case study is described in section 3. Results and discussion are presented in section 4, followed by a summary and conclusions in section 5.

2. Proposed Adaptive, Multiobjective Optimal Sequencing Approach

The philosophy underpinning the proposed approach is to add consideration of deep uncertainty to the traditionally used approach to obtaining optimal urban water supply augmentation sequences, which is based on the optimization of a set of objectives subject to the satisfaction of water supply security constraint(s). An approach based on this philosophy enables decision makers to explore the impact of the consideration of deep uncertainty on optimal sequences of water supply augmentation options by identifying dynamic adaptive pathways, rather than a single optimal solution, which is in alignment with approaches based on adaptive dynamic planning [*Haasnoot et al*., 2013, 2014; *Kwakkel et al*., 2014]. This philosophy is also in keeping with that used in scenario-based decision-making, 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]. This is in contrast to flexible optimal sequencing approaches that have been developed for water distribution system design [*Basupi and Kapelan*, 2013] and flood management [*Woodward et al*., 2013], in which uncertain future conditions are represented by probability distributions, thereby explicitly weighting the likelihood of different outcomes, rather than representing a set of alternative future states of the world [*Mahmoud et al*., 2009]. Consequently, the proposed approach is more likely to be able to cater to deep uncertainty. However, it is acknowledged that the proposed approach also has a number of limitations, such as a potential loss of mathematical optimality, as discussed in section 2.5.

In line with the underpinning philosophy outlined above, the proposed optimal sequencing approach for urban water supply augmentation under deep uncertainty consists of three steps (see Figure 1), namely, (i) identification of a *diverse portfolio* of optimal water supply augmentation sequence plans *over the entire planning period* with the aid of scenario-based multiobjective optimization in order to identify solutions that are optimal under a range of plausible future conditions (catering to dynamic robustness over the entire planning horizon); (ii) assessment of the performance of the portfolio of optimal sequence plans in terms of *robustness* and *flexibility* over the *current staging interval* and *variation of the optimization objectives* over the *entire planning period* (catering to static robustness during those periods of the planning horizon when no changes can be made to the system and to consideration of adaptation at a minimal loss of optimality); and (iii) selection of the water supply augmentation option(s) to be implemented at the *current decision stage* based on the trade-offs between the performance criteria in (ii). The above steps are repeated at subsequent decision stages (e.g., if the staging interval is 10 years, this process is repeated every 10 years) (Figure 1). Details of each of these steps are given in the following sections. It should be noted that the proposed approach could be easily adapted to other long-term water resources sequencing or scheduling applications.

2.1. Identification of Diverse Portfolio of Optimal Water Supply Augmentation Sequence Plans

When identifying a set of optimal solutions under deep uncertainty, it is critical to identify a portfolio of potential solutions that are able to respond to different future conditions [*Korteling et al*., 2013]. In order to achieve this, it is proposed to use a formal multiobjective optimization approach to develop independent optimal sequence plans over the entire planning horizon (e.g., 50 years) for a number of scenarios representing different combinations of uncertain variables affecting future conditions. As shown in Figure 1 (Step 1a), the first step in the process involves the formulation of the optimization problem, including selection of

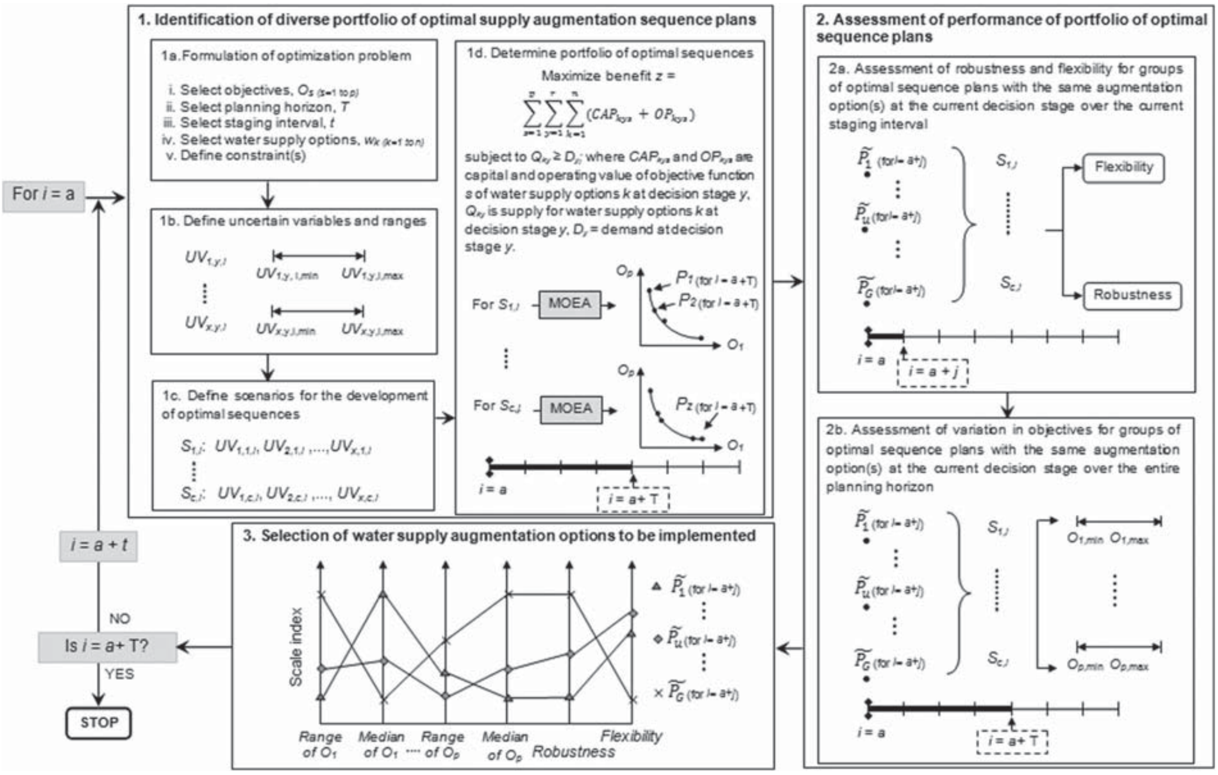

Figure 1. Diagrammatic representation of proposed adaptive, multiobjective optimal sequencing approach under deep uncertainty.

the objectives to be optimized (e.g., minimize cost and minimize greenhouse gas emissions) ($O_{s(s=1\ to\ p)}$), selection of the planning horizon (i.e., the period over which optimal sequence plans are to be developed) (T), selection of the staging interval (i.e., the interval at which the addition of potential water supply augmentation options is considered) (t), selection of the water supply augmentation options (i.e., the decision variables) ($W_{k(k=1\ \text{to}\ n)}$) and definition of the constraint(s) (i.e., that some measure of supply is greater than or equal to some measure of demand, in addition to any constraints on the decision variables). The number of decision stages, y, can be calculated as $y=(T+t)/t$). It should be noted that it is suggested to only consider discrete water supply augmentation options, as this is what would generally be considered in practice.

Next, the uncertain variables need to be selected ($UV_1, UV_2, \ldots, UV_x$). As the optimization problem addressed here is the optimization of the selected objectives subject to supply being greater than or equal to demand, the critical uncertainties are in relation to the satisfaction of this constraint, and are therefore likely to be variables that affect supply and demand (e.g., rainfall, temperature, evaporation, and population). As shown in Figure 1 (Step 1b), the ranges of the uncertain variables need to be defined for each of the decision stages y at the current time period i ($UV_{1,y,i}, UV_{2,y,i}, \ldots, UV_{x,y,i}$), followed by the selection of scenarios that consist of different combinations and values of the uncertain variables ($S_{1,i}, S_{2,i}, \ldots, S_{c,i}$) (Figure 1, Step 1c). It should be noted that the ranges of the uncertain variables, as well as the selection of the scenarios, should reflect current best knowledge in relation to the plausible changes of these variables over the planning horizon.

The use of scenario analysis is considered most appropriate for determining the portfolio of diverse solutions, as it enables alternative plausible future dynamic pathways to be developed in line with the philosophy that underpins the proposed approach, as outlined earlier. It should be noted that the different scenarios are not designed 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]. For this reason, scenario analysis has been adopted widely as a means of assessing the impact of deep uncertainty in water resources planning [*Kasprzyk et al.*, 2012, 2013; *Matrosov et al.*, 2013a, 2013b]. Most scenario development involves people from different disciplines and organizations [*Mahmoud et al.*, 2009] and can be achieved using informal [see e.g., *Kasprzyk et al.*, 2012; *Lany et al.*, 2013] or more formal [see e.g., *Leenhardt et al.*, 2012; *Lempert and Groves*, 2010; *Mahmoud et al.*, 2009; *Matrosov et al.*, 2013b] approaches.

Once the problem has been formulated and the uncertain variables and scenarios defined, the portfolios of Pareto-optimal sequences over the entire planning horizon (i.e., from $i = a$ to $i = a + T$) can be obtained. As shown in Figure 1 (Step 1d), as part of the optimization process, the benefit associated with the capital (*CAP*) and operating (*OP*) values are maximized over the p objectives, y decision stages, and n water supply options subject to the supply provided by the selected water supply options at a particular decision stage (Q_{ky}) being greater than or equal to the demand at that decision stage (D_y), as suggested by *Beh et al.* [2014].

For the optimization engine, it is recommended to use multiobjective evolutionary algorithms (MOEAs). This is because they have proved to be flexible and powerful tools for solving complex water resources problems [*Nicklow et al.*, 2010] and are able to identify solutions that represent multiobjective trade-offs in a single optimization run, without the need to provide relative weights for the various objectives. Additionally, EAs have been found to perform well in a number of urban water resources applications [*Cui and Kuczera*, 2003; *di Pierro et al.*, 2009; *Mortazavi et al.*, 2012; *Newman et al.*, 2014]. EAs can also be linked directly with simulation models of the water supply system under consideration, enabling interactions between different water sources to be taken into account, which is an important consideration [*Matrosov et al.*, 2013b]. Further details of the advantages of EAs are given in *Maier et al.* [2014].

As part of the optimization process, separate deterministic optimal sequence plans are generated over the entire planning horizon for each scenario (Figure 1, Step 1d), as was undertaken by *Housh et al.* [2013] and *Kang and Lansey* [2014]. The objective function values of each sequence at each decision point are calculated with the aid of a simulation model of the resulting water supply system, which includes any existing, as well as the proposed, water supply sources. The simulation model is also used to check that supply is greater than or equal to demand throughout the planning horizon. Each staging interval of each sequence is simulated separately in order to cater to the potential incorporation of additional water supply options at each of the decision points. At the end of the optimization process, an approximation to the Pareto front [*Pareto*, 1896] of sequence plans for the scenario under consideration is obtained, which represents the best feasible trade-offs between the selected objectives. The solutions on the Pareto fronts for the different scenarios constitute the desired diverse portfolio of optimal water supply augmentation sequence plans (Figure 1, Step 1d).

2.2. Assessment of Performance of Portfolio of Optimal Sequence Plans

Even though it is important that optimal sequence plans are obtained over the *entire* planning horizon, decisions in relation to which options are *actually implemented* are only made for the *current* staging interval. For example, although optimal sequence plans might be developed for 40 years, if the staging interval is 10 years, only the first set of decisions of the 40 year plan is fixed now, while the rest of the plan can be *adapted* before the next set of decisions about which water supply augmentation option(s) to implement has to be made in 10 year time. Consequently, the members of the portfolio of optimal sequence plans are grouped prior to performance assessment so that members of each group have the same augmentation option(s) at the *current* decision stage ($\tilde{P}_1, \tilde{P}_2, \ldots, \tilde{P}_u, \ldots, \tilde{P}_G$), where $\tilde{P}_u$ is the uth group of sequence plans that have the same augmentation options at the current decision stage, and G is the number of groups of optimal sequence plans with unique water supply augmentation options at the current decision stage (Figure 1, Step 2), which are determined by inspection of all optimal sequence plans. In this way, it is recognized that only decisions about which options to implement at the current decision stage need to be made at this time. However, optimality over the entire planning horizon is taken into account by only considering options at the current decision stage that are part of optimal sequence plans for the entire planning horizon. This concept of identifying optimal solutions over the planning horizon for different scenarios and focusing on the implementation of options at the first decision stage is similar to that followed by *Housh et al.* [2013] and *Kang and Lansey* [2014].

Although the optimal sequence plans that are part of a particular group have the same solution at the current decision stage, they have different solutions at subsequent decision stages, as they are drawn from different parts of the Pareto front (i.e., they represent different trade-offs between objectives) or from different Pareto fronts (i.e., they are optimal for different scenarios) and therefore represent different plausible future dynamic pathways that need to be assessed and explored. In order to achieve this, the performance of each of these pathways is assessed in terms of (i) the implications for water supply security until further changes can be made to the system (see Figure 1, Step 2a—robustness), (ii) the implications on the ability to provide optimal solutions for different scenarios (see Figure 1, Step 2a—flexibility), and (iii) the potential implications on objective function values (see Figure 1, Step 2b), as discussed in subsequent sections.

2.2.1. Assessment of Robustness and Flexibility Over Current Staging Interval

Robustness. The system that is fixed now will be exposed to uncertain conditions over the current staging interval (e.g., over the next 10 years). Consequently, although all current-stage augmentation options satisfy the constraint that supply is greater than or equal to demand for the scenario for which this option is optimal, to the degree to which water supply security of each of the unique current-stage solutions is adequate under all different scenarios until further changes can be made to the system needs to be assessed. This is achieved by assessing the static robustness of the different unique water supply augmentation options at the current decision stage (i.e., of the optimal sequence plans that form part of each of the groups $\left(\tilde{P}_1, \ \tilde{P}_2, \ \ldots, \ \tilde{P}_u, \ \ldots., \ \tilde{P}_G\right)$ for all scenarios ($S_{1,i}, S_{2,i}, \ldots, S_{c,i}$) *over the current staging interval* (i.e., before there is an opportunity to make further changes to the system) (Figure 1, Step 2a).

In order to measure robustness, a number of different metrics can be used [*Hashimoto et al*., 1982; *Kasprzyk et al*., 2013; *Korteling et al*., 2013; *Matrosov et al*., 2013a, b], all of which reflect some measure of insensitivity to future conditions and the ability to perform satisfactorily over a broad range of future conditions. As part of the proposed approach, the measure of robustness used by *Paton et al*. [2014a, b] is used:

$$Robustness_u = \frac{R_{uc}}{c}, \tag{1}$$

where R_{uc} is the number of scenarios for which group $\tilde{P}_u$ of the optimal sequence plans is considered to exhibit acceptable performance over the current staging interval and c is the total number of uncertain scenarios. A desirable property of this measure of robustness is that it considers each scenario as an independent plausible future and provides information on the fraction of scenarios for which a particular solution performs at an acceptable level from a water supply security perspective. Which performance levels are considered acceptable are case study dependent, but could include potential water supply security measures such as reliability, resilience and vulnerability, as recommended by *Yazdani et al*. [2011], or the risk of water shortages, as suggested by *Hall et al*. [2012]. It should be noted that, as the solutions at the current staging interval are identical for each of the groups of optimal sequence plans ($\tilde{P}_1, \tilde{P}_2, \ldots, \tilde{P}_G$), robustness only has to be calculated once for each group.

Flexibility. Given the adaptive nature of the proposed approach, the flexibility that the supply augmentation options that are fixed at the current decision stage provide in terms of being able to be part of optimal long-term sequence plans in the face of uncertain future conditions is also important. As stated in *Mejia-Giraldo and McCalley* [2014], a "solution is flexible when it can be adapted cost-effectively to *any* of the conditions characterizing the identified scenarios." From this perspective, a solution is more flexible if it is optimal for a larger number of scenarios and less flexible if is optimal for a smaller number of scenarios. Consequently, *Flexibility* is defined as the fraction of the scenarios for which group $\tilde{P}_u$ solutions at the current decision stage are optimal as follows:

$$Flexibility_u = \frac{C_{p_u}}{c}, \tag{2}$$

where Cp_u is the number of scenarios for which a particular set of augmentation options(s), $\tilde{P}_u$ is selected over the current staging interval, and c is the total number of uncertain scenarios. Therefore, a flexibility of 1 indicates that the solution that is fixed at the current decision stage is part of optimal sequence plans for *every* scenario and can therefore be part of optimal solutions under the full range of plausible future conditions considered. In contrast, a flexibility of $1/c$ indicates that the solution that is fixed at the current decision stage is only optimal for *one* of the c future scenarios. If this solution is implemented and the single scenario for which this solution is optimal does not occur, any changes to the sequence plan over the planning horizon will result in a loss of optimality, as another plan will be optimal. It should be noted that flexibility is calculated for each group of optimal sequence plans ($\tilde{P}_1, \tilde{P}_2, \ldots, \tilde{P}_u, \ldots, \tilde{P}_G$) (see Figure 1, Step 2a).

2.2.2. Assessment of Variation in Objectives for the Selected Scenarios Over the Entire Planning Horizon

In addition to the assessment of robustness and flexibility of $\tilde{P}_u$ ($i = 1, 2, \ldots, G$), it is important to consider the central tendency and spread of the objective function values of all of the different optimal sequence plans that are part of a group over all scenarios. In order to achieve this, it is proposed to use the *median* and *range* of the objective functions ($O_1, O_2, \ldots, O_p$) over the entire planning horizon. It should be noted that the median and range are suggested as measures of central tendency and variation, rather than alternative measures, such as the expected value and standard deviation, as the scenarios represent different plausible futures, rather than events of a certain probability. In order to obtain the required values of median and range, the objective functions are calculated for each member of a particular group of optimal sequence plans over all scenarios. These calculations are repeated for each group of optimal sequence plans $\tilde{P}_u$ ($i = 1, 2, \ldots, G$) so that values of the median and range are obtained for each objective for each of the groups (see Figure 1, Step 2b).

2.3. Selection of Water Supply Augmentation Options to be Implemented

Finally, the most appropriate group of optimal sequence plans, and hence the water supply augmentation option(s) to be implemented at the current decision stage, needs to be selected. When dealing with multiple, competing objectives, there is generally no single optimal solution, but a collection of solutions that are all optimal [*Pareto*, 1896]. This is because for these solutions, 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 solution to be implemented has to be selected based on user preferences of the trade-offs between the median and range of the objectives over the entire planning horizon (e.g., 50 years) and robustness and flexibility over the current staging interval (e.g., the next 10 years until further changes can be made to the system). It is suggested to use value path plots [*Geoffrion et al.*, 1972] for this purpose, as they are a well-known method for visualizing the trade-offs between performance measures (see Figure 1, Step 3).

It should be noted that the purpose of the proposed approach is not to suggest a single best solution, but to provide the best possible information on solutions that represent alternative future pathways to decision makers. This is in line with other approaches that follow a similar philosophy as that underpinning the proposed approach [e.g., *Kasprzyk et al.*, 2013; *Kwakkel et al.*, 2014]. As mentioned above, selection of the option to be implemented is based on user preferences and should involve input from affected stakeholders. If the number of objectives (p) and the number of groups of optimal sequence plans with the same augmentation options at the current decision stage (G) is relatively small, this could be done informally. However, when the product of p and G is large, the use of more advanced visual analytics [see e.g., *Kollat and Reed*, 2007; *Reed and Kollat*, 2013], which is limited to about six or seven options, or more formal decision-making processes, such as multicriteria decision analysis [e.g., *Hyde and Maier*, 2006; *Korteling et al.*, 2013] or scenario discovery [e.g., *Kasprzyk et al.*, 2012; *Lempert*, 2013] approaches, for example, could be used. However, as mentioned above, the focus of this paper is not on the process for selecting the best option, but on the provision of information to decision makers.

2.4. Adaptive Process

As part of the adaptive process, the general steps outlined in sections 2.1–2.3 are repeated at each decision stage (i.e., every t years (e.g., every 10 years)) (see Figure 1, outer loop). However, there are some differences between decision stages, as illustrated in Figure 1 and summarized below.

As decision points are generally separated by some time (e.g., 10 years), the understanding of the trajectories of the various uncertain variables (e.g., population growth and climate futures) is likely to have changed from one decision point to the next. Consequently, the scenarios to be considered in the identification of the portfolio of optimal sequence plans (i.e., $S_{1,i}, S_{2,i}, \ldots, S_{c,i}$) are also likely to be different, as they should be developed based on best available knowledge at the time (see section 2.3).

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While the duration of the planning horizon (e.g., 50 years) remains unchanged, the actual start and end times of the planning horizon over which optimal sequence plans are developed with the aid of multiobjective evolutionary algorithms will be different (i.e., there will be different start and end points) (Figure 1).

2.5. Advantages and Limitations of Proposed Approach

Optimality versus practicality. As mentioned previously, the philosophy underpinning the proposed approach is to enable decision makers to explore the impact of deep uncertainty on urban water supply augmentation sequences that are optimal with respect to the objectives and subject to meeting water supply security constraints, thereby presenting decision makers with plausible future pathways. Consequently, the assessment of the impact of uncertainty on the water supply security constraint via the robustness measure and the assessment of the adaptability of selected solutions to different conditions via the flexibility measure are not included as additional objectives of the optimization problem, but are considered postoptimization. This is in line with other similar approaches to assessing water supply security under deep uncertainty that have not considered the sequencing of options [e.g., *Kasprzyk et al*., 2013].

Apart from the philosophical reasons for not including robustness and flexibility as objectives stated above, there are also practical reasons, as the consideration of robustness and flexibility as objectives would increase the computational effort associated with the optimization considerably. This is because the calculation of robustness and flexibility for each solution at each iteration of the EA requires the results of the optimization runs for all scenarios. This would increase computational effort significantly, especially since the run-times associated with the integrated model of the water resources system can be quite long. Furthermore, repeated model runs with different stochastically generated hydrological inputs are required in order to obtain a rigorous assessment of water supply security [see *Mortazavi et al*., 2012], thereby increasing run-times even further.

Despite the advantages outlined above, consideration of robustness and flexibility post-optimization, rather than as objectives in the optimization problem, can also be considered a limitation, as this could result in solutions with reduced robustness and flexibility, since these measures are not optimized. In other words, the proposed approach identifies the relative robustness and flexibility of solutions that are optimized for the objectives, but does not necessarily identify solutions that are optimally robust and flexible. However, for the urban water supply augmentation problem and robustness measure considered here, the solution for the worst-case scenario will, by definition, always have a robustness of 1 (i.e., the largest possible, and hence optimal, value). Nevertheless, identification of the best possible trade-offs between robustness and the other performance measures are not guaranteed. In relation to flexibility, an alternative measure, such as regret costs [see *Kang and Lansey*, 2014], could have been used and included more formally in the optimization process, thereby improving the mathematical optimality of the solutions. However, such an approach would be geared toward identifying a single optimal solution, rather than presenting decision makers with alternative pathways.

The approach of presenting decision makers with different future pathways by obtaining separate optimal solutions for each scenario could also result in a loss of mathematical optimality, as a solution that is optimal for a particular scenario might not be optimal if all scenarios are considered simultaneously, as was done by *Kang and Lansey* [2014]. However, it should be noted that the flexibility criterion introduced in this paper provides an indication as to whether or not this is the case. For example, if the flexibility criterion is equal to 1, then there is no loss of optimality, as a particular solution is optimal across all scenarios. In contrast, if the flexibility is less than 1, there will be some loss of optimality. However, the magnitude of this loss cannot be quantified in terms of objective function values using this criterion. It should also be noted that as *Kang and Lansey* [2014] used a compromise cost function to obtain an optimal solution across all scenarios, rather than presenting alternative pathways to decision makers, there is likely to be a trade-off between achieving mathematical optimality and presenting options to decision makers.

Another factor that could result in a loss of mathematical optimality is the fact that the proposed approach uses discrete values of the water supply augmentation options. However, from a practical perspective, urban water supply augmentation options are generally discrete in nature (e.g., whether to implement a particular augmentation option or not or what capacity a particular augmentation option should be), so this is unlikely to present any problems from a practical perspective.

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Single objective versus multi objective. As mentioned previously, compared with other approaches to solving similar problems [*Housh et al*, 2013; *Kang and Lansey*, 2014; *Ray et al*., 2012], the proposed approach is multiobjective, which is an advantage, given that most practical problems have more than one objective. Although *Kang and Lansey* [2014] used an EA as their optimization engine, thereby enabling their approach to be expanded to be multiobjective, this extension has not yet been reported or tested in the literature.

However, the proposed approach also presents a number of challenges due to its multiobjective nature. First, there could be multiple sequence plans with the same solution at the current staging interval that are on the Pareto front for a particular scenario. In this case, only the presence or absence of this solution on Pareto fronts for different scenarios is taken into account in the calculation of flexibility (equation (2)), not the number of optimal sequence plans with this solution, and hence potential losses in trade-off information are not considered in the proposed flexibility criterion. Second, as the number of scenarios for which particular sequence plans are optimal varies, some sequence plans that are Pareto optimal for a particular scenario might be completely dominated in terms of the median and range of the objective function values once the solution has been evaluated over all scenarios, for some of which a solution might not be Pareto optimal. However, this is not a problem from a practical perspective, as such solutions can be discarded as part of the final evaluation process.

3. Case Study

3.1. Background

In order to illustrate and test the utility of the proposed approach, it is applied to a case study based on the southern region of the Adelaide water supply system (WSS) in 2010. Adelaide is the capital city of South Australia (SA) (see Figure 2) and has a 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. Recorded annual rainfall ranges from 257 to 882 mm [*Maier et al*., 2013]. Average annual mains water consumption was estimated to be 163 gigalitres (GL) in 2008 [*Government of South Australia*, 2009].

This case study is selected as it has been used as a benchmark in previous water resources studies. *Paton et al*. [2013] assessed the impact of climate change on the water supply security of this system and concluded that supply augmentation was needed. *Paton et al*. [2014b] assessed the utility of a small number of water supply augmentation options in terms of PV of cost and water supply security and *Paton et al*. [2014a] used a multiobjective optimization approach to explore the trade-offs between PV of cost, PV of greenhouse gas emissions and water supply security for different supply augmentation options and operating policies. However, the *sequencing* of water supply augmentation options was not considered in any of these studies. The optimal sequencing problem for this system was addressed by *Beh et al*. [2014], but they used an approximate problem formulation in conjunction with a linear programming method, did not use a truly multiobjective approach and did not consider the impact of uncertainty (i.e., the optimal sequencing problem was considered to be deterministic).

The southern Adelaide WSS (see Figure 2) supplies around 50% of the demand of metropolitan Adelaide. In 2010, the system was supplied by 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 from the River Murray is based on a 5 year rolling license for Adelaide, which is fixed at 650 GL. Of this, half is assumed to be allocated to the southern Adelaide WSS. The Happy Valley reservoir is a service reservoir that stores water transferred from Mount Bold reservoir prior to treatment at the Happy Valley water treatment plant.

As highlighted by *Paton et al*. [2013], supply augmentation is required for the southern Adelaide WSS to meet future demands in the face of increased water demand and climate change impacts. In this study, the potential augmentation options identified by the SA government are considered, including a desalination plant at Port Stanvac, various storm water harvesting schemes, and household rainwater tanks (Figure 2) [*Government of South Australia*, 2009]. It should be noted that long-term demand management options have already been applied extensively in the case study system and are therefore not considered. However, supply shortfalls that can be accommodated by temporary water restrictions are included as part of the

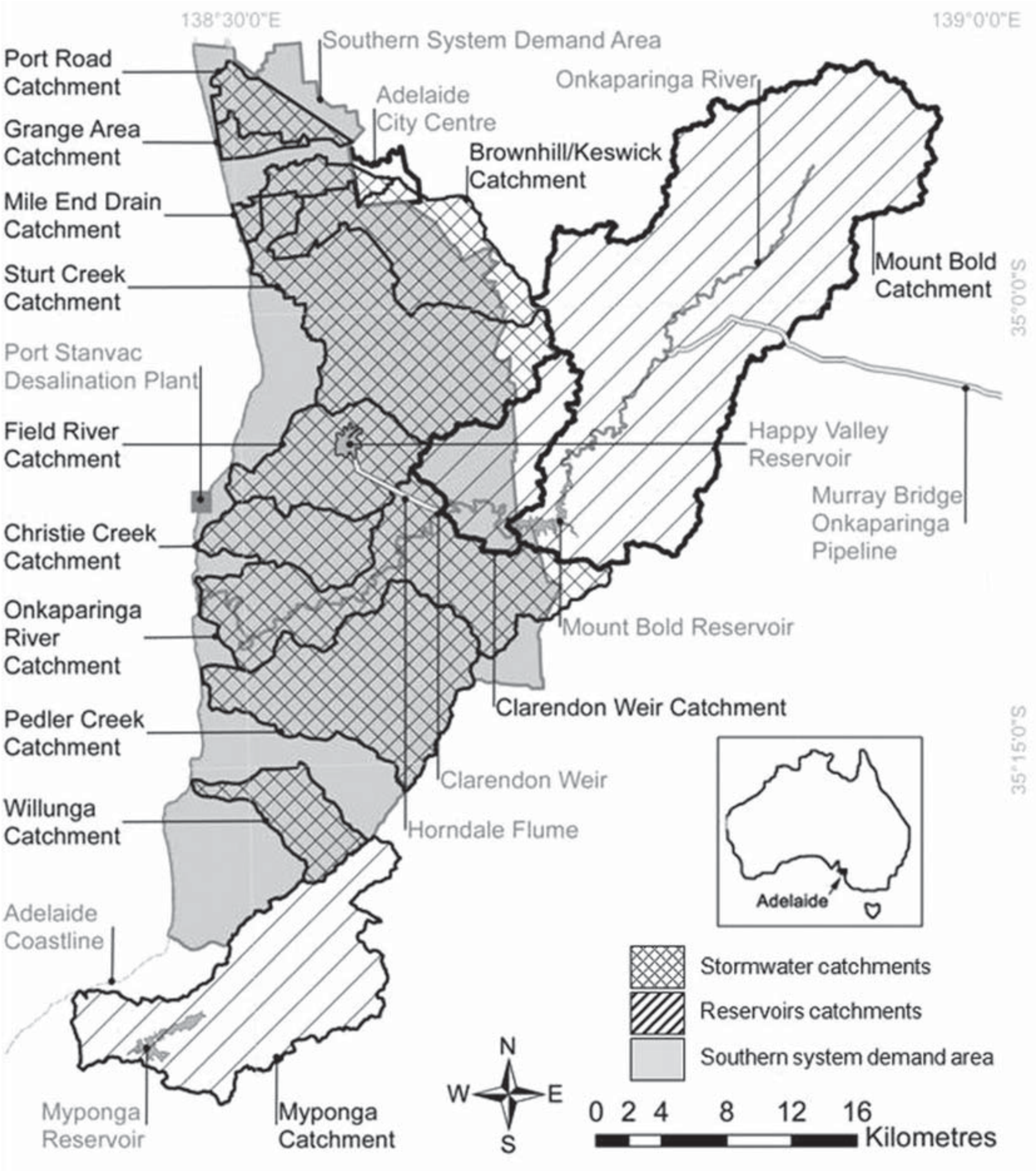

Figure 2. Map of the Southern Adelaide water supply system (WSS).

acceptability criterion for the robustness calculations (see section 3.3.2). Augmentation of existing sources is also excluded as options, as there is limited potential for additional supply from these sources.

3.2. Overall Experimental Approach

In line with the objectives stated in section 1, the overall purpose of the experimental approach is to demonstrate the application of the proposed approach to the Adelaide case study and to test the utility of the adaptive features of the proposed approach by comparing its performance with that of an equivalent static approach. A summary of the overall experimental approach is given in Figure 3. Part A in Figure 3 corresponds to the application of the proposed approach to the Adelaide case study and is aligned with the general approach introduced in section 2 (Figure 1). Part B in Figure 3 corresponds to the assessment of the

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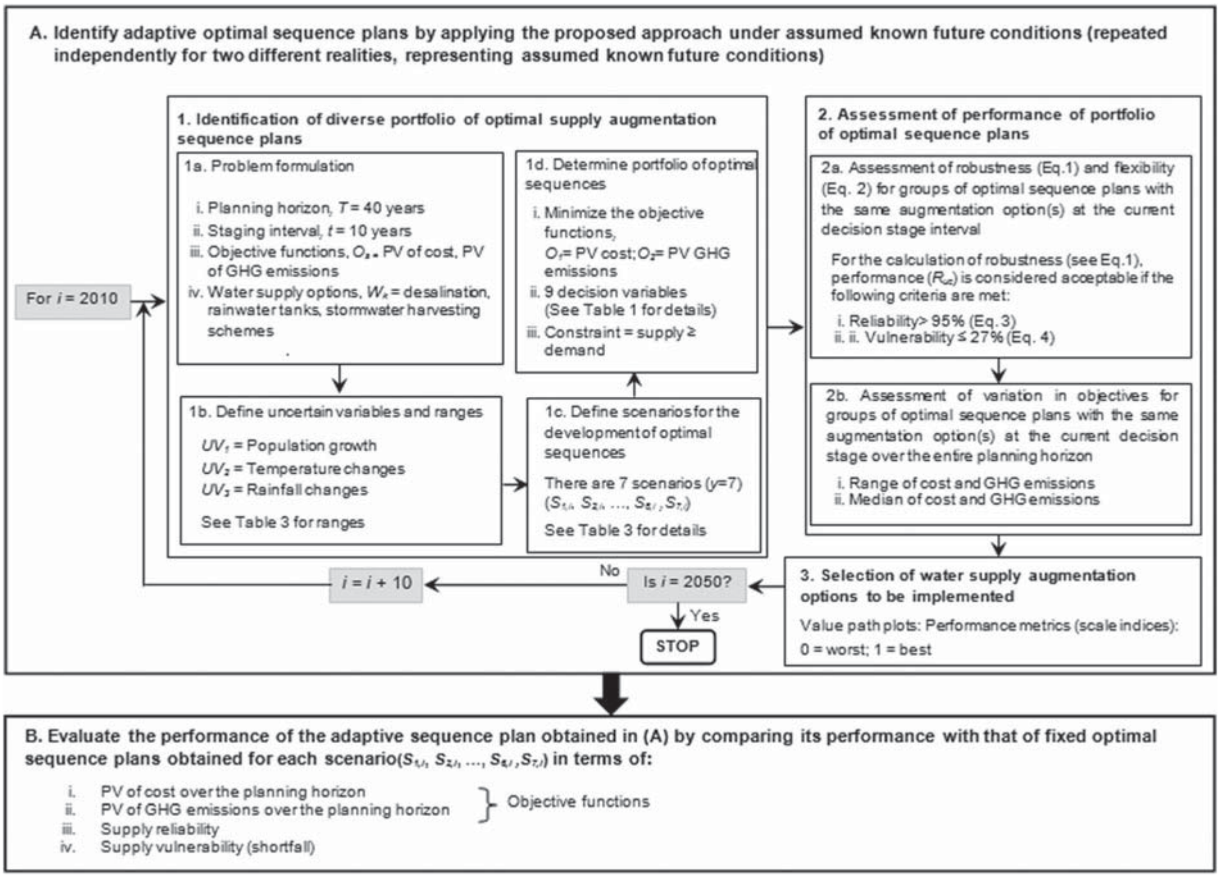

Figure 3. Summary of experimental approach for the Adelaide case study.

utility of the adaptive features of the proposed approach by comparison with an equivalent static approach.

As it is only possible to evaluate the true utility of the adaptive nature of the proposed approach over the actual duration of the planning horizon (e.g., over the next 40 years), the proposed experimental approach is based on assumed known future conditions (or simulated realities) and the simulation of what would actually happen over the adopted planning horizon under these conditions (Figure 3, Part A). In other words, steps 1–3 of the proposed approach (Figures 1 and 3, Part A) are implemented at 2010 to determine which supply augmentation option(s) to implement at this time. Next, it is assumed that 10 years have passed and that it is known what the actual values of the uncertain variables at this time are and that the corresponding updated estimates of the ranges of the uncertain variables and scenarios are known. Steps 1–3 of the proposed approach are then repeated to determine which supply augmentation option(s) to implement at the simulated current time (i.e., 2020). This whole process is then repeated for 2030, 2040, and 2050 for a particular reality in accordance with the adaptive nature of the proposed approach (Figures 1 and 3, Part A).

In order to demonstrate that the proposed adaptive approach results in different augmentation options under different sets of actual future conditions, the entire process in Part A of Figure 3 is repeated for a different set of assumed known future conditions. These two sets of assumed known future conditions are referred to as Reality 1 and Reality 2. In other words, two sets of independent results are presented for two alternative simulated realities for the sake of comparison of how different augmentation options can be obtained by using the adaptive approach based on different changes in actual future conditions. It should be noted that the realities are different from the scenarios. However, the realities represent actual known future conditions (i.e., what has actually happened), which are assumed for the purposes of the computational experiments for testing the utility of the adaptive features of the proposed approach presented in this paper (Figure 3, Part B), the scenarios represent plausible future conditions at the time of decision making and are an integral part of the proposed approach (Figure 3, Part A).

In order to assess the utility of the adaptive nature of the proposed approach, the augmentation options obtained using the proposed adaptive approach are compared with an equivalent static approach [e.g., *Mortazavi-Naeini et al.*, 2014], as all current approaches to the optimal sequencing of urban water supply augmentation options are not adaptive, as discussed in section 1 (Figure 3, Part B). Consequently, the static approach provides a benchmark of current best practice in literature against which to assess the adaptive features of the proposed approach. The static approach is implemented for each of the plausible scenarios to provide a comprehensive basis of comparison.

The comparison of the adaptive and static approaches is conducted over the two independent realities. As the purpose is to assess how well the sequence plans obtained using the proposed adaptive approach and the benchmark static approach perform under the two realities, and not which approach performs best for a given reality, the performance metrics for a particular sequence are averaged over the two realities. This enables the performance of a selected sequence to be assessed in the face of the occurrence of two different actual future conditions, which are unknown at the time of decision making.

Details of the implementation of the above approach for the case study based on the southern Adelaide WSS are given in the subsequent sections, with Part A of Figure 3 corresponding to section 3.3 and Part B to section 3.4.

3.3. Identification of Optimal Sequence Plans

The details for steps 1–3 of the proposed approach (Figure 1) for the Adelaide case study are summarized in Part A. of Figure 3 and described below. As mentioned above, this process is repeated for each of the two independent realities for the sake of assessing the utility of the adaptive features of the proposed approach.

3.3.1. Identification of Diverse Portfolio of Optimal Supply Augmentation Sequence Plans

Problem formulation (Figure 3*, Part A, section 1a)*. A 40 year planning horizon and a 10 year staging interval are adopted. Therefore, there are five decision stages over the 40 year planning horizon (i.e., 2010, 2020, . . ., 2050). However, as these years correspond to the first year of the 40 year planning horizon, a total time period of 80 years is considered (i.e., 2010–2050, 2020–2060, . . ., 2050–2090).

The selected objectives include the minimization of the present value (PV) of economic cost and the PV of greenhouse gas (GHG) emissions. GHG emissions are considered as an objective in addition to the most commonly used objective of cost minimization due to an increased awareness of the need to reduce the carbon footprint associated with water supply systems [*Wu et al.*, 2010a, 2010b, 2013; *Paton et al.*, 2014a]. GHG emissions are of particular concern for the southern Adelaide system because water is pumped significant distances from the River Murray and because desalination is considered as an alternative source of water [see *Beh et al.*, 2014; *Paton et al.*, 2013, 2014a, 2014b]. Note that gross GHG emissions are used in this study. These may be fully or partially offset by the purchase of green power or other carbon offsets.

Both the PV of cost and the PV of GHG emissions consist of two components, namely capital and operating values. Capital costs and GHG emissions are incurred at the construction phase of a project (e.g., materials and outlay), while operating values are incurred over the life of a project (e.g., electricity for pumping and maintenance). A discount rate of 6% is used for the calculation of the PV of cost, as suggested by *Wu et al.* [2010b]. In contrast, a discount rate of 1.4% is used for the calculation of the PV of GHG emissions, as this has been suggested as being appropriate for stabilizing GHG concentrations in the atmosphere within a desired range [*Wu et al.*, 2010a]. The capital emissions values are computed using embodied energy [*Treloar*, 1995] and emission factor analysis [*Wu et al.*, 2010a]. Further details are provided in *Beh et al.* [2014] and *Paton et al.* [2013, 2014a, b].

The existing water supply options (i.e., the three reservoirs and supply from the River Murray) are included in all sequence plans at the beginning of the planning horizon. However, the desalination plant, storm water harvesting schemes and household rainwater tanks are considered as potential additional water supply sources at each decision point.

Table 1. Details of Decision Variable Formulation

Decision Variable	Description	Lower Limit	Upper Limit	Estimated Yield	Capital Cost ($)	Unit Operation Cost ($/kL)	Capital GHG Emissions ($kgCO_2$-e)	Unit GHG Emissions ($kgCO_2$-e/kL)
1	50 GL desalination plant implementation stage	0	5	25.0 GL/yr	1,347,000,000	1.00	228,538,000	5.41
2	100 GL desalination plant implementation stage	0	5	50.0 GL/yr	1,830,000,000	1.00	237,103,000	5.43
3	50 GL desalination plant expansion implementation stage	0	5	25.0 GL/yr	483,000,000	1.00	8,565,000	5.41
4	Household rainwater tank implementation stage	0	5					
5	Household rainwater tank size (kL)	1	10	35.0–47.1 kL/yr	2,181–3,560	0.63–0.78	718–4,635	1.22
6	Brownhill and Keswick Creek storm water harvesting scheme implementation stage	0	5	6.3 GL/yr	160,025,000	1.23	7,249,000	2.04
7	Sturt River storm water harvesting scheme implementation stage	0	5	7.0 GL/yr	194,193,000	1.23	7,351,000	2.06
8	Field river storm water harvesting scheme implementation stage	0	5	1.6 GL/yr	35,689,000	1.23	3,576,000	6.05
9	Pedler Creek storm water harvesting scheme implementation stage	0	5	5.0 GL/yr	110,682,000	1.23	5,643,000	1.60

The production capacity of the Port Stanvac desalination plant is either 50 or 100 GL per annum, with the option of a 50 GL per annum expansion of the 50 GL per annum plant. Thus, either a 50 or a 100 GL desalination plant can be selected at any of the decision stages, but not both, and the selected desalination plant cannot be down-sized at later stages. It should be noted that the desalination plant can supply the entire metropolitan Adelaide region, so it is assumed that 50% of its capacity can supply the southern Adelaide WSS. Once one of the desalination options has been selected, it cannot be selected again. However, if the 50 GL desalination plant is selected, expansion to full capacity is allowed at one of the subsequent decision points.

The storm water harvesting schemes considered include Brownhill and Keswick Creek, Sturt River, Field River and Pedler Creek (Figure 2). The potential supply from these schemes is generally different from year to year as a result of hydrologic variability, but their estimated annual yields range from 1.6 to 7.0 GL/yr [*Beh et al*., 2014]. One or more of the schemes can be selected at any of the decision stages. However, each scheme can only be selected once. The amount of water supplied by each scheme during each decision stage is calculated using a simulation model and is a function of rainfall and the interaction with the other selected sources.

Ten potential rainwater tank capacities are considered, ranging from 1 to 10 kL. The potential supply from these tanks is generally different from year to year as a result of hydrologic variability, but their estimated annual yields range from 35 to 47.1 kL/tank/yr [*Beh et al*., 2014]. It is assumed that rainwater tanks with a particular capacity can be implemented at any of the decision stages. However, the option to use rainwater tanks as a source can only be selected once during the planning horizon. 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.

As the quality of the storm water and rainwater is generally not of drinking standard, these sources are assigned to nonpotable uses, whereas supply from the reservoirs and the desalination plant is chosen to provide household indoor use. Further details of the mapping of sources to end-uses and how this was represented in the simulation model are given in *Beh et al*. [2014] and *Paton et al*. [2014a, b].

The decision variables corresponding to the sequencing of the above augmentation options used during the optimization are summarized in Table 1. The estimated yield, capital and unit operating costs and GHG emissions of each water supply options are also given in Table 1 [see *Beh et al*., 2014]. However, these are only estimates and the actual values supplied by each source are calculated with the aid of a simulation model for a particular scenario at a particular decision stage based on the interaction of the different potable and nonpotable demands and the selected mix of supply sources. As the capacities of most of the water supply options are fixed (i.e., desalination, storm water harvesting schemes), the discrete decision variables correspond to the decision stage at which a particular option is implemented, ranging from 0 (i.e., the option is not implemented over the planning horizon) to 5 (i.e., the option is implemented at decision stage 5) (decision variables 1–4 and 6–9, Table 1). However, in addition to a decision variable for timing, rainwater tanks also have an integer decision variable corresponding to rainwater tank capacity (decision variable 5, Table 1), ranging from 1 to 10 kL. It should be noted that the number of rainwater tanks implemented depends on the time of implementation, as the number of households changes with time due to changes in population.

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Table 2. Details of the Two Realities (Assumed Known Future Conditions) Considered (Cumulative Changes)

	2020	2030	2040	2050
Reality 1				
Population growth	7%	13%	18%	22%
Climate change impact				
1. Changes in temperature (°C)	0.25	0.55	0.70	1.00
2. Changes in rainfall	−0.5%	−1.5%	−4.0%	−6.0%
Reality 2				
Population growth	7%	18%	20%	29%
Climate change impact				
1. Changes in temperature (°C)	0.25	0.60	1.00	1.25
2. Changes in rainfall	−0.5%	−3.0%	−6.0%	−9.0%

Definition of uncertain variables and scenarios (Figure 33, Part A, sections 1b and 1c). Population, rainfall and temperature are considered as the uncertain variables ($UV_{1,i}$, $UV_{2,i}$, $UV_{3,i}$) as they have a direct impact on supply and demand. As mentioned in section 3.2, in order to illustrate the benefit of the adaptive nature of the proposed approach, it is applied to two realities, each consisting of different known trajectories of the uncertain variables up to 2050. Reality 1 has a milder and Reality 2 a more severe impact on water supply security in terms of total demand and climate change conditions (see Table 2). The changes in population growth and climate change impact used in the two realities are based on estimates from the *Government of South Australia* [2009] and *Australian Bureau of Statistics* [2013] to ensure they are plausible.

For each reality, seven scenarios ($S_{1,i}$, $S_{2,i}$, . . ., $S_{7,i}$) consisting of different population growth and climate change impacts are used to represent a small number of plausible, but different, future pathways. Scenario 1 represents the best set of plausible future conditions in terms of water supply security with extremely low projected population growth and the least severe future climate change impact. In contrast, Scenario 7 represents the worst set of plausible future conditions with respect to water supply security, with extremely high projected population growth and severe climate change impact. These extremes are considered to ensure the generation of Pareto-optimal solutions that can cater to a wide range of plausible future conditions. Details of the ranges of the uncertain variables for each of the seven scenarios for each of the two realities, representing assumed best knowledge at the time of interest, are given in Table 3. As can be seen, the ranges of the uncertain variables for the different scenarios change over time, thereby representing transient scenarios, as advocated by *Haasnoot et al*. [2013] and *Kwakkel et al*. [2014].

The seven population scenarios for each reality are based on an initial population of 600, 240 for the southern Adelaide region in 2010 [*Australian Bureau of Statistics*, 2011]. For each reality, the seven time series of population projections are based on 40 year annual population projections accounting for various assumptions of fertility, mortality, net interstate migration and net overseas migration [*Australian Bureau of Statistics*, 2013].

Table 3. Uncertain Variable Options for Each Scenario and Reality (Cumulative Changes)

	2010–2050			2020–2060			2030–2070			2040–2080			2050–2090		
	Population Growth (%)	Temperature Change (°C)	Rainfall Change (%)	Population Growth (%)	Temperature Change (°C)	Rainfall Change (%)	Population Growth (%)	Temperature Change (°C)	Rainfall Change (%)	Population Growth (%)	Temperature Change (°C)	Rainfall Change (%)	Population Growth (%)	Temperature Change (°C)	Rainfall Change (%)
Reality 1															
Scenario 1	−2.80	0.80	−7.60	−1.20	0.94	−7.70	−13.60	1.06	−8.60	−35.20	1.16	−9.30	−69.20	1.25	−10.00
Scenario 2	8.00	0.80	−7.60	16.40	0.94	−7.70	13.20	1.06	−8.60	−20.00	1.16	−9.30	−18.40	1.25	−10.00
Scenario 3	18.80	1.09	−9.90	17.20	1.31	−10.40	9.20	1.52	−11.80	−26.40	1.66	−12.80	−21.60	1.71	−13.10
Scenario 4	29.60	1.09	−9.90	8.40	1.31	−10.40	9.60	1.52	−11.80	6.80	1.66	−12.80	0.00	1.71	−13.10
Scenario 5	40.80	1.09	−9.90	20.00	1.31	−10.40	32.00	1.52	−11.80	38.80	1.66	−12.80	41.20	1.71	−13.10
Scenario 6	51.60	1.29	−11.60	30.80	1.41	−11.90	52.00	1.57	−12.20	66.80	1.72	−13.10	76.80	1.91	−14.30
Scenario 7	62.80	1.29	−11.60	34.00	1.41	−11.90	58.00	1.57	−12.20	75.60	1.72	−13.10	88.40	1.91	−14.30
Reality 2															
Scenario 1	−2.80	0.93	−9.40	35.20	1.08	−10.80	61.20	1.22	−12.00	81.20	1.33	−13.00	97.60	1.44	−13.90
Scenario 2	8.00	0.93	−9.40	38.40	1.08	−10.80	67.20	1.22	−12.00	90.00	1.33	−13.00	108.80	1.44	−13.90
Scenario 3	18.80	1.26	−12.30	39.20	1.51	−12.50	70.00	1.75	−13.70	96.00	1.92	−14.40	118.40	1.97	−14.80
Scenario 4	29.60	1.26	−12.30	40.00	1.51	−12.50	73.20	1.75	−13.70	102.40	1.92	−14.40	128.00	1.97	−14.80
Scenario 5	40.80	1.26	−12.30	42.80	1.51	−12.50	77.60	1.75	−13.70	107.20	1.92	−14.40	133.20	1.97	−14.80
Scenario 6	51.60	1.49	−14.30	45.60	1.63	−15.50	81.60	1.81	−16.50	112.00	1.98	−17.80	138.40	2.19	−18.30
Scenario 7	62.80	1.49	−14.30	51.60	1.63	−15.50	96.80	1.81	−16.50	138.00	1.98	−17.80	176.80	2.19	−18.30

The seven rainfall and temperature scenarios for each reality are based on different combinations of SRES scenarios (A1FI, A1T, A2, B1, and B2) and Global Circulation Models (GCMs) (CCSM3, CGCM3.1, CSIRO-MK3.5, FGOALS-g1.0, MIROC3.2 (hires), MIROC3.2 (medres), and MRI-CGCM2.3.2), as suggested by *Paton et al*. [2013] for the case study area. Based on the outputs of different combinations of SRES scenarios and GCMs, the climate change impacted daily rainfall and evaporation data are obtained by multiplying the 40 year historical rainfall and evaporation data used in the simulation model by the appropriate climate change factor obtained from OzClim (http://www.csiro.au/ozclim/), as was undertaken by *Paton et al*. [2013] for the case study area.

As discussed in section 2.1, in practice, the scenarios would be developed with the aid of stakeholders with different backgrounds and from different organizations. However, in this case, the above scenarios are assumed for the sake of illustration of the proposed approach. However, the scenarios are selected carefully to represent a range of plausible and very different future conditions. In addition, the different scenarios are not necessarily equally likely, as some represent combinations of extreme conditions, while others do not.

Determination of portfolio of optimal sequences (Figure 3*, Part A, section 1d)*. *WaterCress* (*Water-C*ommunity *R*esource *E*valuation and *S*imulation *S*ystem) is used as the simulation model for calculating the objective functions and checking demand constraints. *WaterCress* is a water balance model that enables simulation of a real life layout of a water supply system as an assembly of its components. Each component has an associated database which contains all variables (e.g., demand, rainfall, and 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, and (iii) can incorporate less conventional water supply sources (e.g., desalination and recycled water). Furthermore, the model is freely available and was developed specifically for South Australian conditions. Further details of the *WaterCress* model developed for the case study WSS are given in *Beh et al*. [2014] and *Paton et al*. [2014a].

Total demand is calculated as a function of population size, per capita demand and commercial and industrial demand. Population is considered as one of the uncertain variables, as detailed above. Average household size is assumed to be constant at 2.3 people and per capita demand is held constant at 491 L/p/d over the planning horizon [see *Beh et al*., 2014], as variability in population has been shown to have by far the greatest impact on water supply security for this system [*Paton et al*., 2013].

For each of the two realities, the multiobjective optimization process is repeated for each scenario at each of the five decision points. The Water System Multiobjective Genetic Algorithm (WSMGA) [*Wu et al*., 2010a] is used as the optimization engine, as it is based on the widely used multiobjective genetic algorithm NSGA-II [*Deb et al*., 2002], is able to cater to integer decision variables, and has been used successfully in a number of multiobjective optimization studies of water systems [*Paton et al*., 2014b; *Wu et al*., 2010a, 2010b, 2013]. In order to obtain the best possible values of the parameters controlling GA searching behavior, a number of preliminary trials are conducted. The optimal values are found to be a population size of 150, a probability of crossover of 0.9 and a probability of mutation of 0.1. Hypervolume convergence is used as the termination criterion, as this is one of the most popular measures for capturing the diversity, as well as the convergence, of solutions in multiobjective optimization problems [*Reed et al*., 2013; *Zitzler*, 1999].

3.3.2. Assessment of Performance of Portfolio of Optimal Sequence Plans

For a particular reality and decision stage, all solutions on the Pareto fronts for the seven scenarios are analyzed and grouped so that each group contains the same augmentation option(s) at the current staging interval (see section 2.2) and all solutions in each of these groups are assessed in terms of robustness, flexibility and variation of the median and range of the PV of cost and PV of GHG emissions over all scenarios, as detailed below.

3.3.2.1. Assessment of Robustness and Flexibility

Robustness is calculated in accordance with equation (1) (see section 2.2) (Figure 3, Part A, section 2a). In equation (1), the performance of the water supply system is considered acceptable when reliability (equation (3)) is greater than 95% and the maximum vulnerability (equation (4)) is less than or equal to 27% of demand. This latter figure is equal to the projected savings under Adelaide's highest Level 5 water restrictions [*Chong et al*., 2009].

As suggested by *Beh et al*. [2014] and *Paton et al*. [2014a, 2014b], hydrologic variability is accounted for by using 20 replicates of daily stochastic rainfall for each rainfall station. These stochastic rainfall series are generated for each scenario using the Stochastic Climate Library (SCL) (www.toolkit.net.au/scl). Further details of the generation of the stochastic rainfall time series are given in *Paton et al*. [2013] and *Beh et al*. [2014]. Consequently, the reliability and vulnerability values used in the robustness calculations are the average values obtained for the 20 stochastic rainfall sequences for the next staging interval as follows:

$$Reliability = \frac{\sum_{k=1}^{m}\left[\left(\frac{T_s}{T_i}\right)\right]_k}{m}, \tag{3}$$

where T_s is the number of years for which supply meets demand, T_i is the length of the selected staging interval (years), and m is the number of stochastic sequences.

$$Vulnerability = \frac{\sum_{k=1}^{m}\left[maximum\left(\frac{D_y}{S_y}\right)\right]_k}{m}, \tag{4}$$

where D_y is the volume of annual supply shortfall, as obtained from the *WaterCress* model, and S_y is the total annual demand, as obtained from the *WaterCress* model.

3.3.2.2. Assessment of Variation in Objectives

The median and range of the PV of cost and the PV of GHG emissions are obtained by calculating the PV of cost and PV of GHG emissions for all Pareto optimal solutions for all scenarios and calculating the required statistics for all solutions belonging to a particular group (i.e., with the same solution at the current staging interval) (Figure 3, Part A, section 2b). This is achieved with the aid of the *WaterCress* model.

3.3.3. Selection of Water Supply Augmentation Options to be Implemented

The water supply augmentation option(s) to be implemented at a particular decision stage are selected based on informal consideration of the trade-offs between the performance metrics (i.e., robustness, flexibility, median and range of PV of cost, and median and range of PV of GHG emissions), as illustrated in value path plots (Figure 3, Part A, section 3). It should be noted that all indices of the performance metrics are scaled from zero to one, where one is the best and zero the worst value.

It should be noted that in practice, more formal decision-making processes are likely to be used, including stakeholder input and a clear articulation of the relative importance of the criteria, potentially using some of the methods mentioned in section 2.3. However, this is not been undertaken here, as the main purpose is to illustrate the information obtained by applying the proposed approach and the selection of options has been made by weighing up the trade-offs between the assessment criteria.

3.3.4. Application to Different Decision Stages Under Different Realities (Known Future Conditions)

As shown in Figure 3, steps 1–3 outlined in sections 3.3.1–3.3.3 are implemented for five decision stages starting at 2010, 2020, 2030, 2040, and 2050, using the different scenarios outlined in Table 3. The entire process is also repeated for the two independent realities, as explained earlier (see Tables 2 and 3) for the purpose of being able to simulate the performance of the proposed approach under different actual conditions and enabling the assessment of the utility of the adaptive features of the proposed approach.

3.4. Evaluation of Adaptive Optimal Sequence Plans

As mentioned in section 3.2, in order to assess the utility and potential benefits of the proposed adaptive approach, the *actual* performance of the optimal *adaptive* sequences obtained for the two realities is compared with that of *static* optimal sequences obtained for the different scenarios at the beginning of the planning horizon in terms of optimization objectives and *actual* water supply security (i.e., reliability and vulnerability) (Figure 4, Part B). It should be noted that for each of the optimal sequence plans, the NPV of cost and GHG emissions are calculated for the entire planning horizon (as there is a single plan), while reliability and vulnerability are calculated for each staging interval, as they change over the planning horizon as different augmentation options come online. In accordance with the overall approach outlined in section 3.2, the overall performance of the sequences obtained using the proposed adaptive and the benchmark static approaches is compared by averaging the performance measures over the two realities.

4. Results and Discussion

The results are presented in two sections, including an illustration of the development of the adaptive optimal sequence plans for a single time step (Part A of Figure 3, section 4.1) and the evaluation of the utility of the adaptive features of the proposed approach (Part B of Figure 3, section 4.2).

4.1. Development of Adaptive Optimal Sequence Plans

In this section, the results for each of the three major steps of the proposed approach (i.e., Steps 1, 2, and 3 in Figures 1 and 3a) are presented for the first decision stage (i.e., 2010) for illustration purposes (sections 4.1.1–4.1.3). The optimal sequences obtained by simulating application of the proposed approach over an actual period of 40 years (i.e., from 2010 to 2050) for the two different realities are presented in section 4.1.4. The optimal augmentation options for 2020, 2030, 2040, and 2050 for both realities are based on the types of results presented in sections 4.1.1–4.1.3, which are included as supporting information. It should be noted that in real life, an optimal sequence, such as that presented in section 4.1.4, would be developed over 40 years, with application of the three steps in the proposed process and analysis of the results occurring every 10 years, resulting in the selection of the augmentation option(s) to implement at the current decision stage. In practice, there would only be a single reality and the two different realities are simulated here for the purposes of assessing the utility of the adaptive features of the proposed approach, as explained previously.

4.1.1. Identification of Diverse Portfolio of Optimal Sequence Plans (2010–2050)

The Pareto fronts of optimal sequence plans for the seven scenarios for 2010–2050 are shown in Figure 4. As can be seen, the optimal augmentation sequences required to ensure supply is greater than or equal to demand for the seven scenarios result in significant differences in the PV of cost and the PV of GHG emissions. This is as expected, as greater supply augmentation is required for the scenarios that include greater population growth and more severe climate change impacts, resulting in higher PV of costs and PV of GHG emissions. These increased values of the objective function values are generally due the selection of a larger number of augmentation options or their implementation at an earlier stage in the planning horizon. Consequently, by using scenarios that represent a wide range of plausible future conditions, a diverse portfolio of optimal sequence plans is obtained, each representing different trade-offs between the objectives and different abilities to provide water supply security under a variety of future conditions.

4.1.2. Assessment of Performance of Portfolio of Optimal Sequence Plans (2010)

The Pareto-optimal solutions in Figure 4 contain six unique solutions at the current staging interval (2010–2020), resulting in six groups of optimal sequence plans, as shown in Table 4. As can be seen, one solution consists of no augmentation of the existing water supply, while the other five options consist of different combinations of storm water harvesting schemes.

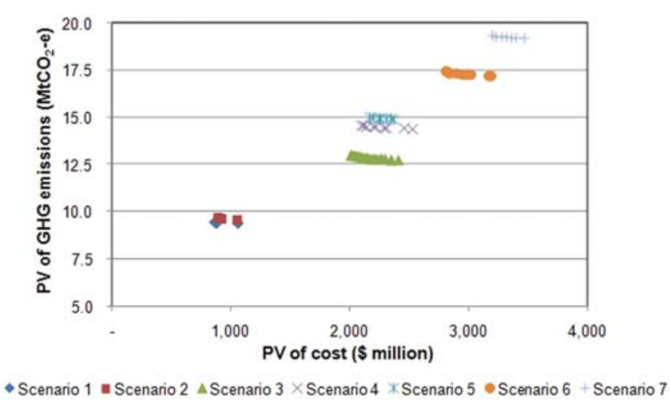

Figure 4. Trade-off between the present value of GHG emissions and the cost for the seven projected possible future scenarios (2010–2050).

The results of the performance assessment of the six groups of optimal sequence plans are given in Figure 6. As can be seen, there is significant variation in PV of cost and PV of GHG emissions when the optimal sequence plans that are part of a particular group are exposed to the conditions represented by all scenarios. As expected, robustness increases as the capacity of the augmentation options increases. For example,

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Table 4. Unique Solutions at the Current Staging Interval (2010–2020) for Decision Stage 1

	Decision Stage at Which to Implement Water Supply Options for t = 2010 (1 = Implemented at t = 2010)								
Group	50 GL Desalination Plant	100 GL Desalination Plant	50 GL Desalination Expansion	Rainwater Tank	Tank Size	Brownhill and Keswick Creek Storm Water Harvesting Scheme	Sturt River Storm Water Harvesting Scheme	Field River Storm Water Harvesting Scheme	Pedler Creek Storm Water Harvesting Scheme
$\tilde{P}_1$									
$\tilde{P}_2$									1
$\tilde{P}_3$						1			
$\tilde{P}_4$							1		
$\tilde{P}_5$						1			1
$\tilde{P}_6$							1		1

group 1 does not have any supply augmentation and therefore has the lowest robustness, groups 2–4 include the addition of a single storm water harvesting scheme, resulting in increases in robustness and groups 5 and 6 include the addition of two storm water harvesting schemes, resulting in maximum levels of robustness. As can be seen, the flexibility of the augmentation options in Table 4 is highly variable, with some solutions part of optimal sequences for all seven scenarios, while others are only part of optimal sequence plans for two of the seven scenarios.

4.1.3. Selection of Water Supply Augmentation Option(s) to be Implemented (2010)

The value path plot corresponding to the results in Figure 5 is given in Figure 6. As can be seen, although the optimal sequence plans in groups 1 ($\tilde{P}_1$) and 2 ($\tilde{P}_2$) perform very well in terms of the median of PV of cost and flexibility, they perform poorly across the other criteria, with clearly the worst performance in terms of the range of the PV of cost, the range of the PV of GHG emissions and robustness. The optimal sequence plans in groups 4 ($\tilde{P}_4$) and 6 ($\tilde{P}_6$) have high levels of robustness, but this comes at the expense of high median PV of cost. Although these solutions perform well in terms of the range of PV of cost, they perform poorly in terms of the median and range of PV of GHG emissions and relatively poorly in terms of flexibility. The optimal sequence plans in groups 3 ($\tilde{P}_3$) and 5 ($\tilde{P}_5$) tend to perform well across all performance criteria. They clearly outperform all other groups in terms of the median and range of the PV of GHG emissions and

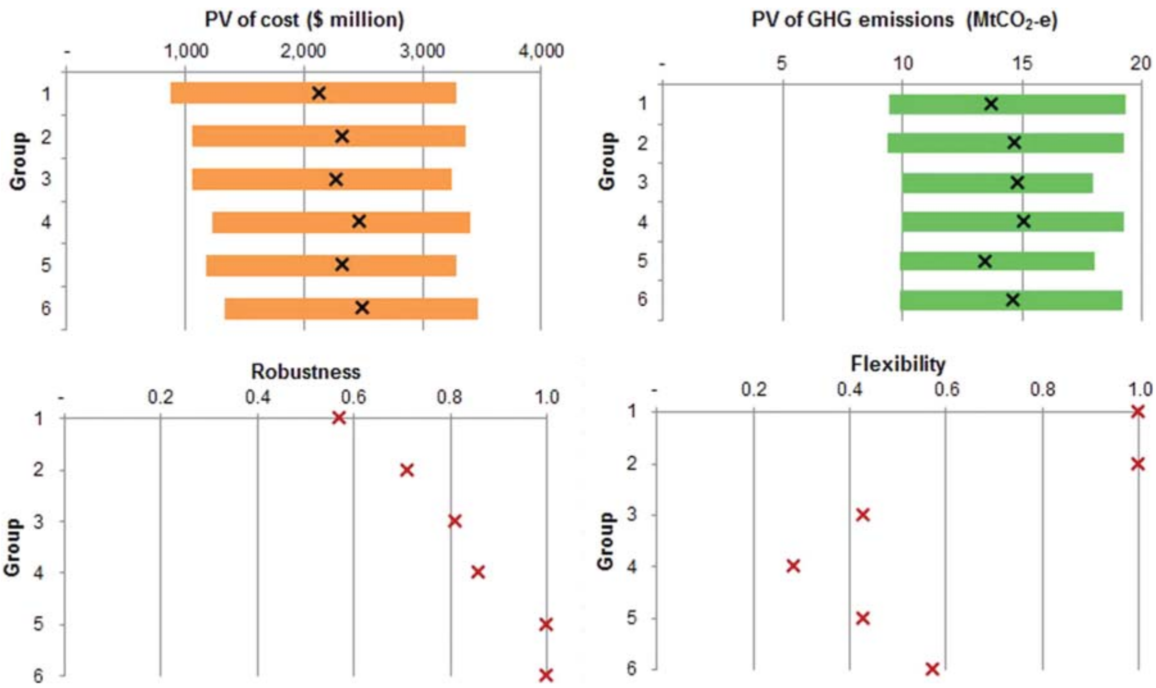

Figure 5. Results of performance assessment for groups with the same solution at 2010.

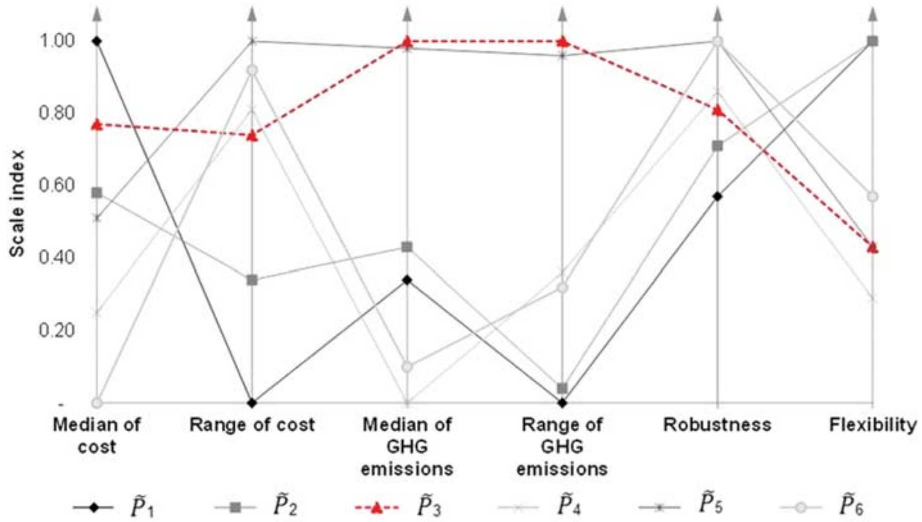

Figure 6. Results of performance assessment for decision stage 1 (realities 1 and 2). The value path of the selected option is highlighted in red.

perform well in terms of robustness and median and range of PV of cost. Their performance in terms of flexibility is at the lower end of the spectrum, but the plans that perform best in terms of flexibility tend to perform worst in terms of robustness.

As discussed previously, the selection of which option to implement at the current decision stage depends on the priorities of the stakeholders involved. In the absence of such stakeholder input, for the purposes of illustrating the proposed approach in this paper, the sequence plans belonging to group 3 are selected as they provide good trade-offs between the performance criteria. Consequently, the Brownhill and Keswick storm water harvesting scheme is chosen to be implemented at the first decision stage and fixed for the subsequent decision stages (see Table 4).

4.1.4. Selected Optimal Sequence Plans

The optimal sequences obtained by applying the proposed approach under the two simulated realities over the entire planning horizon and their corresponding objective function values are given in Table 5. As mentioned previously, each of these sequences would be developed over a period of 40 years in practice, going through the process illustrated in sections 4.1.1–4.1.3 for the first decision stage (see supporting information for results for other decision stages). As can be seen, there are significant differences between the two optimal sequences as a result of the different actual and forecast populations, rainfalls and temperatures that characterize the two realities, as well as the ability of the proposed approach to adapt to these different conditions over time. This confirms that the proposed approach is successful in adapting to changing conditions.

For both simulated realities, the 50 GL desalination plant and the Brownhill and Keswick storm water harvesting schemes are implemented. However, the desalination plant is implemented earlier for Reality 2. In addition, the 50 GL desalination plant expansion and the Sturt River and Pedler Creek storm water harvesting schemes are implemented under the more severe conditions of Reality 2 in order to be able to satisfy demand. As can be seen from Table 5, the NPV of cost of the optimal sequence plan for Reality 2 is about 1.5 times that of the optimal sequence plan for Reality 1, whereas the corresponding ratio of the NPV of GHG emissions is approximately 1.2.

4.2. Utility Adaptive Features of Proposed Approach

The *average* values of the reliability and vulnerability of the water supply systems corresponding to the implementation of (i) the sequences obtained using the proposed adaptive optimal sequencing approach and (ii) the fixed optimal sequence plans for each scenario under the *actual conditions* experienced as part of the two simulated realities, with the associated average PV of cost and GHG emissions are shown in Table 6. As can be seen, the performance of the sequences obtained using the proposed adaptive approach is very good

Table 5. Optimal Sequences for the Two Simulated Realities Considered

	Optimal Sequence for Reality 1 and Optimal Sequence for Reality 2										
	50 GL Desalination Plant	100 GL Desalination Plant	50 GL Desalination Expansion	Rainwater Tank	Tank Size	Brownhill and Keswick Creek Storm Water Harvesting Scheme	Sturt River Storm Water Harvesting Scheme	Field River Storm Water Harvesting Scheme	Pedler Creek Storm Water Harvesting Scheme	PV of Cost ($ million)	PV of GHG Emissions ($MtCO_2$-e)
Optimal adaptive plan for Reality 1	3	0	0	0	0	1	0	0	0	1,537.26	12.15
Optimal adaptive plan for Reality 2	2	0	5	0	0	1	3	0	3	2,262.42	14.44

compared with that of the static approaches. While the NPV of cost and GHG emissions of the static sequences developed for scenarios 1 (S1) and 2 (S2) are significantly less than those of the adaptive sequences, the corresponding water supply security is not acceptable, with average reliabilities of less than 100% in all but one of the five staging intervals, ranging from 62 to 85%. Similarly, the average vulnerabilities (demand shortfalls) associated with the three staging intervals for which reliability is less than 100% ranges from 11.4 to 16.4%. In contrast, the water supply security of the adaptive plan is excellent, with 100% reliability in three of the five staging intervals and average reliabilities of 92 and 98% for the other two staging intervals and corresponding demand shortfalls of only 3 and 0.5%, respectively. In order to achieve comparable (although slightly worse, see Table 6) levels of water supply security when static sequence plans are considered (S4), the PV of cost increases by $329.77 million (17.4%) and the PV of GHG emissions by 1.25 MtCO2-e (9.4%). In order to achieve better water supply security than that afforded by the adaptive plans (100% reliability for all staging intervals, S6), the PV of cost increases by $982.31 million (51.7%) and the PV of GHG emissions by 2.31 MtCO2-e (17.7%). In addition, when using the static approach, it is unclear which of the seven sequences to implement. Consequently, these results clearly demonstrate the advantage of using the proposed adaptive approach, compared with the corresponding static approach.

5. Summary and Conclusions

In this paper, an adaptive, multiobjective optimal sequencing approach for urban water supply augmentation under deep uncertainty is introduced. As part of the approach, a diverse portfolio of optimal sequence plans is developed for different transient future scenarios using multiobjective evolutionary algorithms.

Table 6. Average Performance of Systems Corresponding to the Implementation of Different Optimal Sequence Plans for Realities 1 and 2

			2010–2020		2020–2030		2030–2040		2040–2050		2050–2060	
	PV of Cost ($ million)	PV of GHG Emissions (MtCO2-e)	Reliability (%)	Vulnerability (%)	Reliability (%)	Vulnerability (%)	Reliability (%)	Vulnerability (%)	Reliability (%)	Vulnerability (%)	Reliability (%)	Vulnerability (%)
Optimal fixed plan (Scenario 1)	900.10	9.74	100	0.0	85	11.4	75	13.25	62	16.4	68	14.15
Optimal fixed plan (Scenario 2)	954.95	9.92	100	0.0	85	11.4	75	13.25	62	16.4	68	14.15
Optimal adaptive plan	1899.84	13.30	100	0.0	98	0.5	100	0.0	92	3.0	100	0.0
Optimal fixed plan (Scenario 3)	2228.51	13.57	100	0.0	100	0.0	100	0.0	92	2.95	83.5	6.35
Optimal fixed plan (Scenario 4)	2229.61	14.55	100	0.0	100	0.0	100	0.0	92	2.95	92	2.2
Optimal fixed plan (Scenario 5)	2254.22	14.60	100	0.0	100	0.0	100	0.0	92	2.95	92	2.2
Optimal fixed plan (Scenario 6)	2882.15	15.66	100	0.0	100	0.0	100	0.0	100	0.0	100	0.0
Optimal fixed plan (Scenario 7)	3187.10	16.59	100	0.0	100	0.0	100	0.0	100	0.0	100	0.0

Next, the robustness and flexibility of the components of the optimal sequence plans that have to be fixed at the current staging interval is assessed for the time period between now and the first opportunity when further changes can be made. In addition, the variability of the objective functions over the entire planning horizon is assessed and the solution that provides the best trade-offs between these criteria, in accordance with stakeholder preferences, is selected. This process is repeated for the next decision stages, when updated information is available. In this way, the approach is able to successfully balance the need for the development of optimal longer-term plans under deep uncertainty with the need to be able to respond to changes as they arise and to provide robust solutions between decision stages. It also provides a computational method in support of the successful implementation of dynamic adaptive planning as a paradigm for dealing with deep uncertainty.

In order to demonstrate the utility of the proposed approach, it is applied to the optimal sequencing of urban water supply augmentation options for a case study based on the southern Adelaide water supply system from 2010 to 2060. In order to illustrate the impact of the adaptive nature of the approach, two different simulated realities are considered. The results indicate that the approach is successful in adapting to changing conditions, while optimizing longer-term objectives and satisfying water supply security constraints along the planning horizon, in highly uncertain planning environments. This is evidenced by the differences in the optimal solutions obtained for the different realities, as well as the favorable performance of the adaptive plans compared with those fixed at the beginning of the planning horizon.

Despite the methodological advances of the proposed approach, there remain a number of avenues for future improvement. First, as mentioned previously, informal approaches to scenario development and the determination of which solution to implement are used. Consequently, the value of using more formal approaches for these steps should be explored, especially for more complex problems and for real-life applications. Second, the problem formulation (e.g., objectives, constraints, and decision variables) is assumed to remain constant throughout the planning horizon, which is unlikely to be the case. Consequently, the incorporation of approaches that enable the problem formulation to be changed over time should be explored [see *Maier et al.*, 2014; *Piscopo et al.*, 2015]. Third, as discussed in sections 2.5, based on the philosophical approach that underpins the proposed method, the solutions obtained might not be mathematically optimal. It would be interesting to assess the impact of this in future studies by comparing the results obtained using the proposed approach with that of *Kang and Lansey* [2014], for example. Finally, although the approach was presented and applied in the context of urban water supply augmentation, it is also applicable to a number of other water resources scheduling and sequencing problems, as mentioned previously. Consequently, it would be useful to tailor and apply the approach presented in this paper to other problem domains.

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