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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

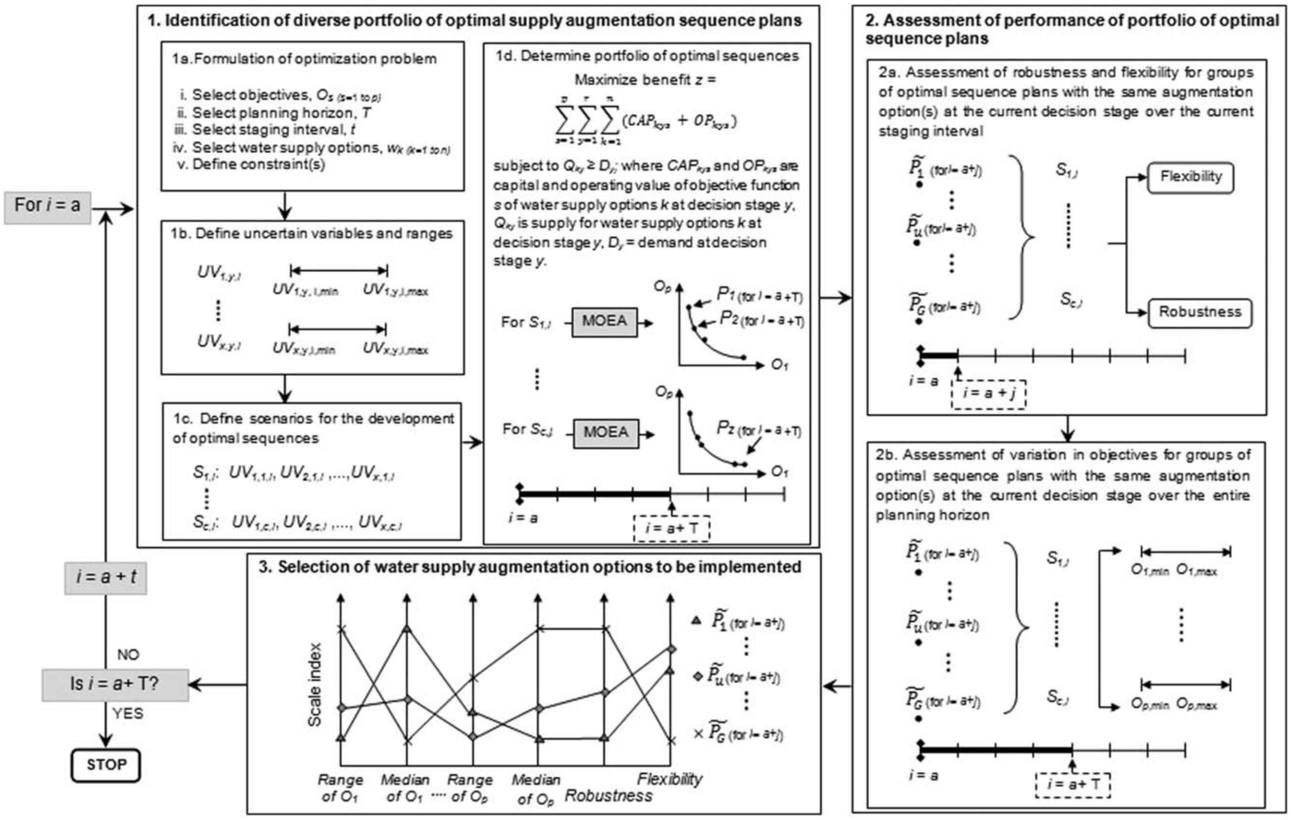

Figure 1. Diagrammatic representation of proposed adaptive, multiobjective optimal sequencing approach under deep uncertainty.

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) ($W_{k(k=1\ to\ n)}$) 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 *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 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

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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).

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.

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

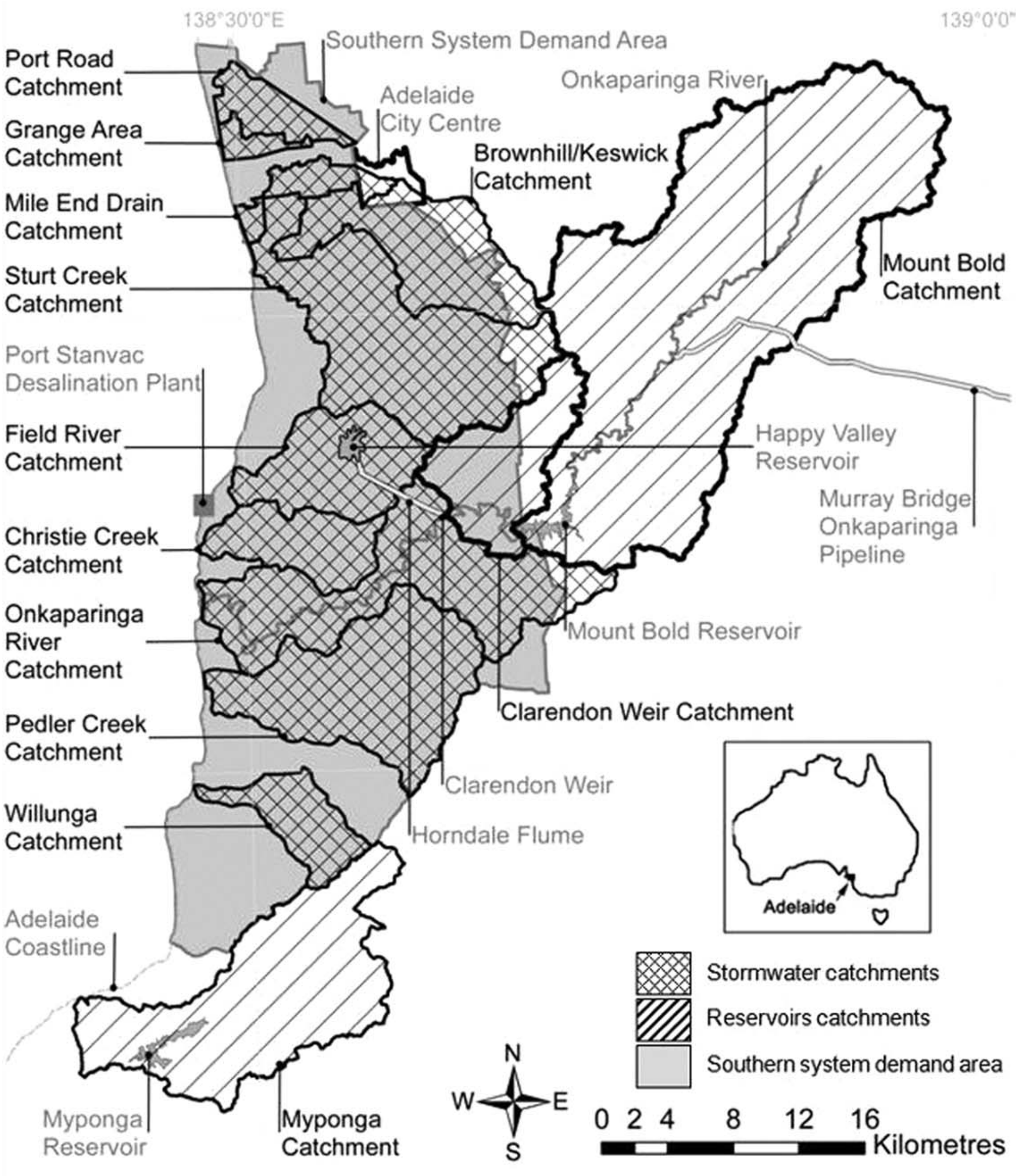

Figure 2. Map of the Southern Adelaide water supply system (WSS).

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

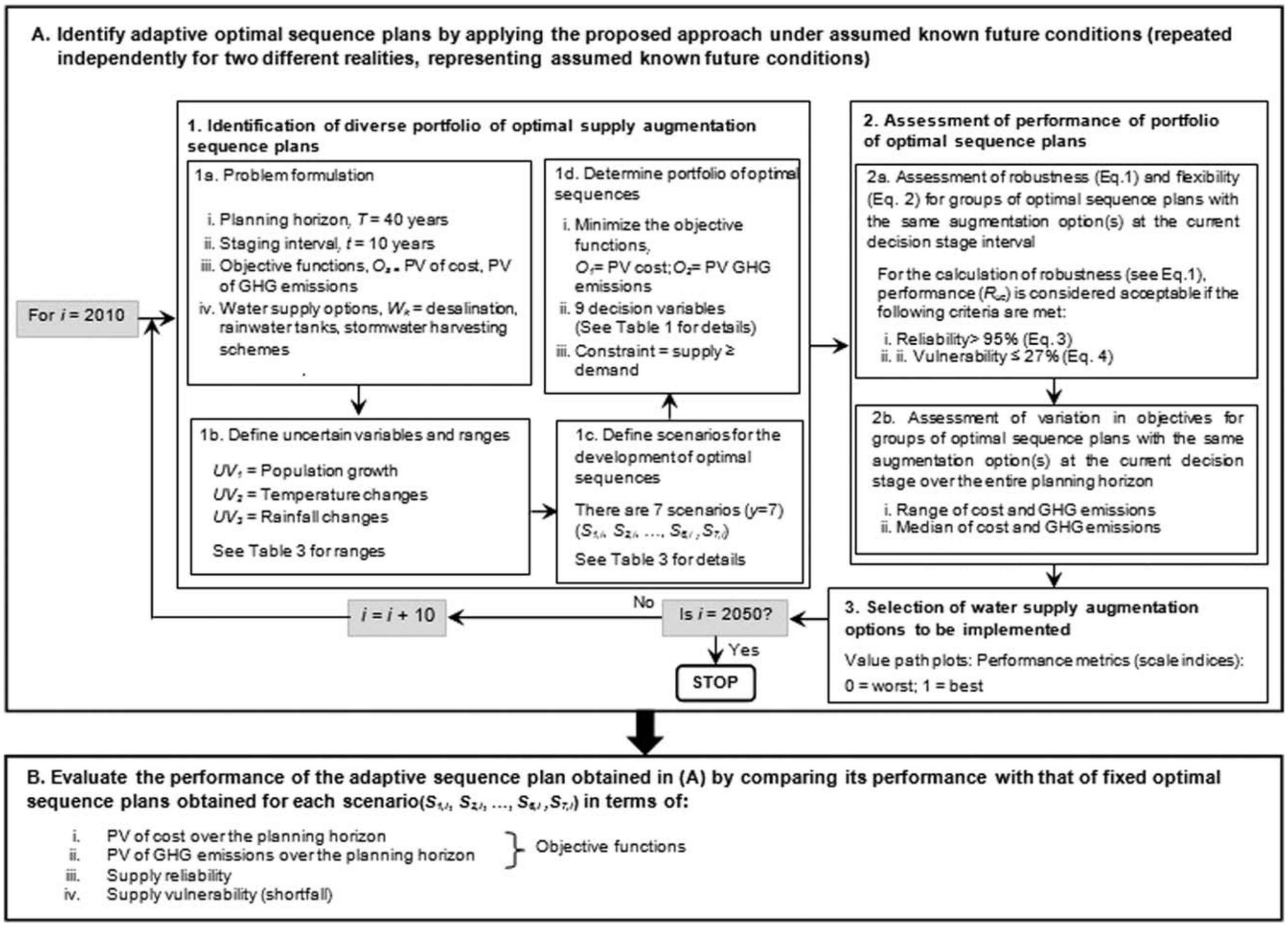

Figure 3. Summary of experimental approach for the Adelaide case study.

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.

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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.

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

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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.

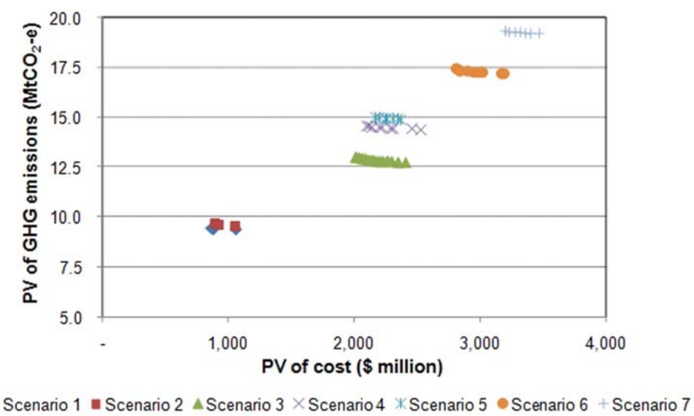

Figure 4. Trade-off between the present value of GHG emissions and the cost for the seven projected possible future scenarios (2010–2050).

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

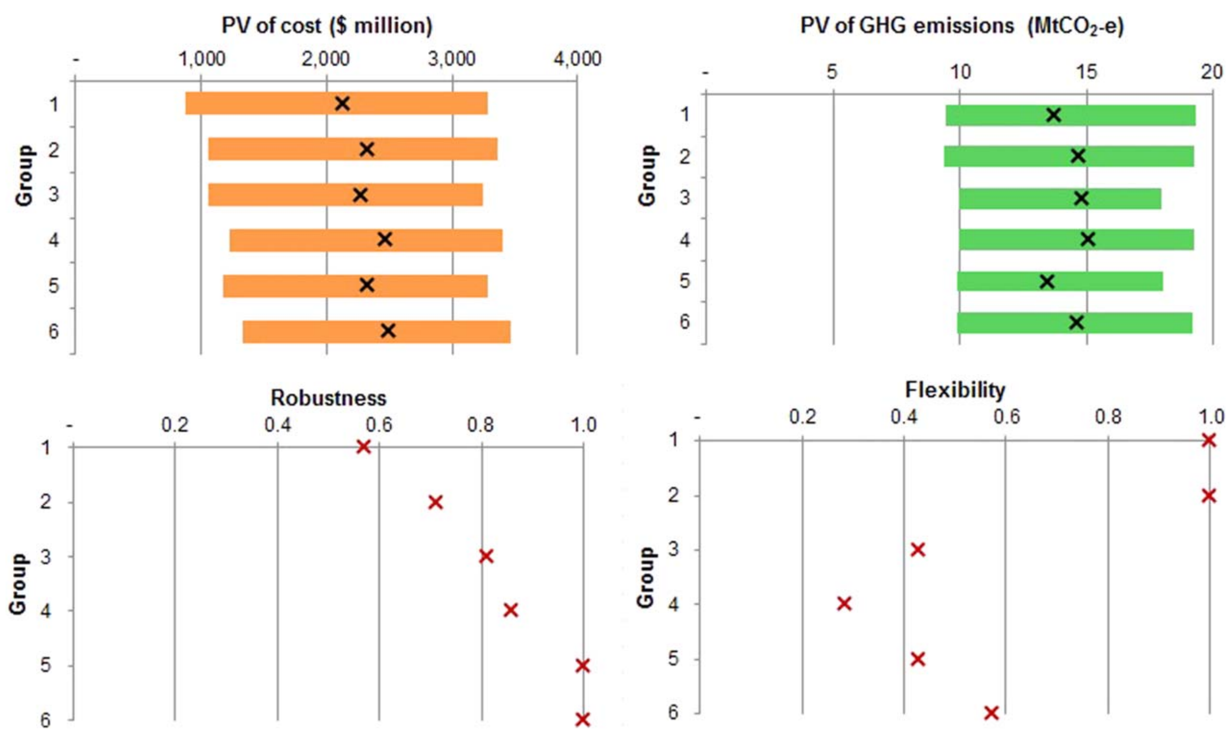

Figure 5. Results of performance assessment for groups with the same solution at 2010.

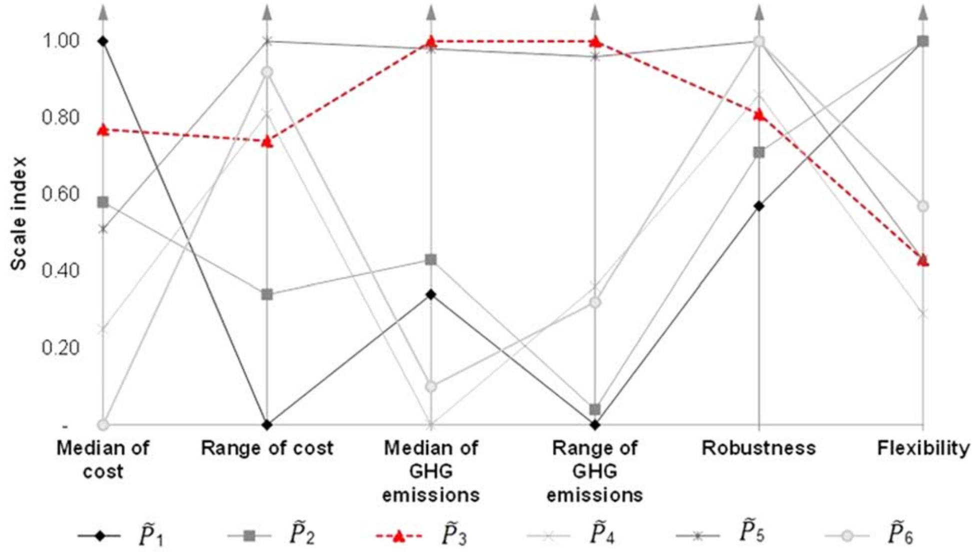

Figure 6. Results of performance assessment for decision stage 1 (realities 1 and 2). The value path of the selected option is highlighted in red.

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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