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Mohammad Mortazavi-Naeini, George Kuczera, Lijie Cui

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- A new formulation for the scheduling capacity expansion problem for urban water
- Use of multiobjective optimization resolves social equity problems
- Demonstrate benefit in jointly optimizing operational and infrastructure options

Correspondence to:
M. Mortazavi-Naeini,
c3069377@uon.edu.au

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Application of multiobjective optimization to scheduling capacity expansion of urban water resource systems

Mohammad Mortazavi-Naeini[1], George Kuczera[1], and Lijie Cui[1]

[1]School of Engineering, University of Newcastle, Newcastle, New South Wales, Australia

Abstract Significant population increase in urban areas is likely to result in a deterioration of drought security and level of service provided by urban water resource systems. One way to cope with this is to optimally schedule the expansion of system resources. However, the high capital costs and environmental impacts associated with expanding or building major water infrastructure warrant the investigation of scheduling system operational options such as reservoir operating rules, demand reduction policies, and drought contingency plans, as a way of delaying or avoiding the expansion of water supply infrastructure. Traditionally, minimizing cost has been considered the primary objective in scheduling capacity expansion problems. In this paper, we consider some of the drawbacks of this approach. It is shown that there is no guarantee that the social burden of coping with drought emergencies is shared equitably across planning stages. In addition, it is shown that previous approaches do not adequately exploit the benefits of joint optimization of operational and infrastructure options and do not adequately address the need for the high level of drought security expected for urban systems. To address these shortcomings, a new multiobjective optimization approach to scheduling capacity expansion in an urban water resource system is presented and illustrated in a case study involving the bulk water supply system for Canberra. The results show that the multiobjective approach can address the temporal equity issue of sharing the burden of drought emergencies and that joint optimization of operational and infrastructure options can provide solutions superior to those just involving infrastructure options.

1. Introduction

In view of the worldwide trend of significant population growth in major cities, it is expected that planners responsible for urban water resource systems will need to cater for a growing demand for water. In addition, they will need to address the challenges arising from future climate change and changing community expectations about level of service and acceptable impacts on environmental systems. In the face of such change, it is expected that the performance of urban water resource systems (as expressed by drought security and level of service) is likely to deteriorate resulting in the need for interventions to augment system resources and improve water use efficiency.

Capacity expansion involves the provision of additional yield by increasing the capacity of existing infrastructure and the construction of new infrastructure harvesting new sources of water. In its simplest manifestation, capacity expansion deals with sizing reservoirs. For example, *Khaliquzzaman and Subhash* [1997] developed a model for sizing multiple reservoirs. *Mousavi and Ramamurthy* [2000] proposed an optimization method to determine the optimal multireservoir system design for water supply by converting two objectives, minimum cost and minimum water deficit, to a single objective function. *Nainis and Haimes* [1975] applied a multilevel approach for capacity expansion in water resource systems; they extended classic benefit-cost analysis, describing their approach as dynamic benefit-cost analysis. *Yang et al*. [2007] applied the concept of multiobjective optimization to reservoir capacity expansion trading off two objectives, minimizing capital costs and minimizing costs arising from water shortages.

Other studies have extended the concept of capacity expansion to include options other than those dealing with sizing reservoirs. For instance, *Nakashima et al*. [1986] developed a two-phase heuristic optimization technique to determine a water supply system layout and to size water production and transmission facilities. *Hsu et al*. [2008] developed a methodology to detect potential bottlenecks in a water distribution system with the aim of facilitating capacity expansion plans. *Dziegielewski et al*. [1992] incorporated drought management plans into their capacity expansion analysis; they assessed the trade-off between long-term and short-term options to manage drought by estimating the expected cost of coping with drought. *Basagaoglu and Yazicigil* [1994] considered capacity expansion in the context of a groundwater system.

All the aforementioned studies have focused on making decisions at the start of the planning period. However, decisions to expand capacity can be implemented at different points of time over the planning period to take advantage of delaying a portion of investment outlays. Although the construction of large infrastructure at the start of the planning period exploits the economies of scale, the time discounting of costs and the uncertain dynamics of growth may nonetheless favor smaller projects staged over the planning period. To analyze this trade-off, a number of studies have considered scheduling expansion [*Braga et al*., 1985; *Chang et al*., 2009; *Gillig et al*., 2001; *Grossman and Marks*, 1977; *Kim and Yeh*, 1986; *Knudsen and Rosbjerg*, 1977; *Lund*, 1987; *Mahmoud*, 2006; *Voivontas et al*., 2003; *Watkins and McKinney*, 1998].

Scheduling expansion problems have typically been formulated to find the timing of predefined projects that minimize the total present worth cost (PWC). Indeed, given this perspective, the main aim is to find the best sequence of projects [*Luss*, 1982]. However, projects often can be implemented at different scales. Thus, the scheduling problem can be generalized to find the optimum timing and scale of predefined projects. This is referred to as the scheduling capacity expansion problem.

A number of studies have investigated the scheduling capacity expansion problem in a water resources context. *Knudsen and Rosbjerg* [1977] developed a general dynamic programming algorithm to find the optimal scheduling of water supply projects. *Kim and Yeh* [1986] introduced a heuristic solution procedure to find an optimal sequence of capacity expansion projects. *Connarty and Dandy* [1996] used genetic algorithm optimization to find the optimum sequence involving nine reservoirs for a case study based on the southeast Queensland headworks system. *Watkins and McKinney* [1998] developed a model involving capacity expansion of an integrated surface and groundwater system. Similarly, *Chung et al*. [2009] applied an optimization model to determine the capacity expansion schedule for groundwater supply. They considered a variety of expansion options involving surface and groundwater sources such as increasing borehole, reservoir, and desalination plant capacity. *Mahmoud* [2006] employed a high dimension dynamic programming model to determine the optimal expansion schedule of a desalination plant. In all these studies, only infrastructure options were considered as decisions. Given there is likely to be interaction between infrastructure and operating rule options, not optimizing operating options jointly with infrastructure options represents a potentially missed opportunity of finding even better solutions.

The high capital costs and environmental impacts associated with expanding or building new major urban water infrastructure warrant the investigation of scheduling system operating rules such as reservoir operating rules, demand reduction policies and drought contingency plans, as a way of delaying or avoiding the expansion of water supply infrastructure [*Lund*, 1987; *Rosenberg et al*., 2008; *Rubinstein and Ortolano*, 1984]. *Rosenberg et al*. [2008] identified the best portfolio of conservation programs, infrastructure expansions, and operational allocations. However, they did not implement any scheduling or sequencing planning in their study. *Lund* [1987] incorporated conservation rules into the scheduling capacity expansion problem. He demonstrated the benefit of using conservation rules to defer water treatment plant expansion. Similarly, *Rubinstein and Ortolano* [1984] presented a framework to determine systematically the optimal combination of demand reduction and supply augmentation projects. In both of these studies, long-term demand reduction such as due to improved efficiency of water-using appliances were considered. A limitation of these studies was their insufficient attention to the issue of drought security. An urban system would be expected to cope/survive extreme droughts with long return periods. If the optimization framework does not "see" such droughts, the optimal solutions are likely to be optimistic and risk the system being vulnerable to severe drought [*Mortazavi et al*., 2012].

In *Lund* [1987], the present worth of conservation cost and capacity expansion cost was minimized to find the optimum time to add new capacity to the system. However, a drawback of this approach is that discounting conservation costs can lead to higher levels of demand reduction in the future than in the present. Similarly, although *Rubinstein and Ortolano* [1984] considered the trade-off between the present worth cost of projects and the expected value of the costs to cope with emergencies, there is no guarantee that the social burden of coping with emergencies is shared equitably across planning stages.

The issue of temporal equity, namely the sharing of the social burden of drought across different planning stages, can be politically and socially sensitive. In such a case, the distribution of equity implicit in a

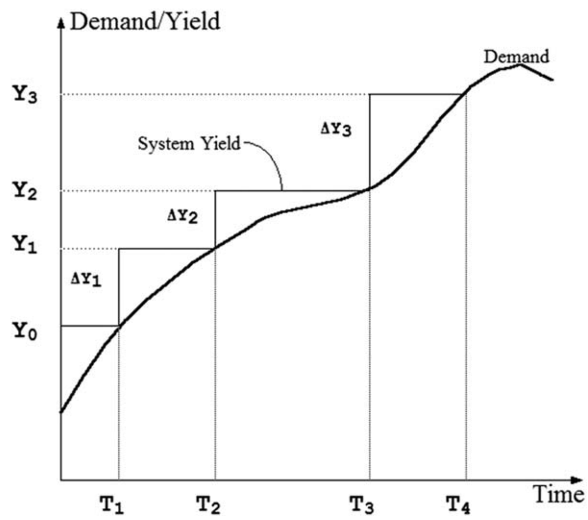

Figure 1. Schematic of scheduling capacity expansion over a planning horizon.

minimization of present worth cost may not be acceptable. *Cai et al.* [2002] recognized this problem when commenting on the difficulty of selecting a discount rate in an analysis of sustainability—indeed they chose to explicitly trade-off measures of efficiency and equity rather than impute the trade-offs associated with a particular discount rate. *Van Liedekerke* [2004] presented a critique of discounting. While acknowledging that the choice of discount rate affects temporal equity, he argued that the distribution of benefits and costs over time should not be determined by selection of a particular discount rate. At the empirical level, there are examples of equity being maintained over time. For example, in NSW, Australia, major water utilities are regulated by operating licenses which, inter alia, define levels of service with regard to reliability of supply and severity of emergencies—of relevance here is that these levels of service remain invariant for different future demand scenarios.

In summary, a number of significant shortcomings have been identified in the reviewed studies. These include the failure to jointly consider the interaction between operating rules and infrastructure decisions, to adequately address drought security and to deal with the issue of equitably sharing the social costs of drought emergencies. These shortcomings are likely to undermine the credibility/relevance of the optimal solutions.

This paper presents a multiobjective optimization approach to scheduling capacity expansion in an urban water resource system that addresses the shortcomings identified in previous studies. The paper is organized as follows: First, a new formulation of the multiobjective scheduling capacity expansion problem is presented. Then using a case study based on the Canberra headworks system, seven scenarios are investigated to demonstrate the significance of the identified shortcomings and how the new approach deals with them.

2. The Multiobjective Scheduling Capacity Expansion Problem

This section presents a formulation of the scheduling capacity expansion problem that addresses the previously identified practically significant shortcomings. To the authors' knowledge, such a formulation has not been previously presented and solved.

2.1. Formulation

We begin with definition of terminology. Figure 1 illustrates an example of the scheduling capacity expansion process. It presents time series of demand and yield (that is, supply that can be sustained with a certain drought security and level of service). Given the initial yield of the system is Y_0, the system can meet demand up to time T_1. At time T_1, a decision is made to add extra yield ΔY_1. As a result, system yield will exceed demand until time T_2. In a similar manner, decisions are taken at later times to provide additional yield. Thus, T_1, T_2, and so on represent change points at which decisions are made. The period between two consecutive change points is called a planning stage.

Suppose the planning period of T years is subdivided into M planning stages with the ith stage commencing at time T_i. To account for climate variability and other stochastic inputs, the inputs to the system are replicated N times over the planning period by sampling from a suitably constructed probability model of the inputs. For each replicate r, q_{tr} is a vector of streamflow and other input values at multiple sites for year

t, and d_{tr} is a vector of unrestricted demand at multiple sites for year t. The notation $Q^r_{u:v}$ denotes the time series of vectors $q_{tr}, t=u, .., v$.

Let $x_i=\{x_i^1, .., x_i^p\}$ denote a p-vector of decision variables that are implemented at the start of the ith planning stage. The decision vector can represent a mix of infrastructure options and operating rules. A solution is defined as a sequence of decision vectors over the M planning stages $x=\{x_1, .., x_M\}$.

The simulation model of the urban water resource system produces N replicates of response denoted by $Z^r_{1:T}=M[x, Q^r_{1:T}, D^r_{1:T}], r=1, .., N$ where $Q^r_{1:T}$ and $D^r_{1:T}$ represent the streamflow (and other inputs) and demand for the rth replicate of the T-year planning period. The performance of the system is evaluated using K objective functions

$$f_i(x)=\sum_{t=1}^{T}\phi(t)E[f_i(Z_{1:t}(x_{1:t}))] \approx \frac{1}{N}\sum_{t=1}^{T}\phi(t)\sum_{r=1}^{N}f_i(Z^r_{1:t}(x_{1:t})), i=1, .., K \quad (1)$$

where $x_{1:t}=\{x_1, .., x_j : T_j \leq t < T_{j+1}\}$ is the sequence of projects or decision vectors implemented on or before year t and $\phi(t)$ is a temporal discounting factor. The term $E[f_i(Z_{1:t}(x_{1:t}))]$ is the expected value of the ith objective function for year t and is evaluated by averaging over the N replicates—the notation emphasizes the fact that the objective function value depends on the response from the simulation model which in turn depends on the decision values.

The multiobjective optimization problem for the scheduling capacity expansion problem involves minimizing the K objective functions over the decision space subject to constraints that include constraints on staging decisions, which are discussed further in section 3.3. This formulation addresses the shortcomings identified in previous applications in the following ways:

1. The use of multiple replicates of input data ensures that drought security can be adequately addressed. *Mortazavi et al*. [2012] dealt with the issue of drought security by choosing an input record with sufficient length to ensure the system could cope with droughts up to a specified return period. However, in the case of scheduling, their approach cannot be used because the planning period T is fixed and because the performance of the system changes over time. The use of multiple replicates of input data provides a solution to this problem. By selecting an appropriate number of replicates N, one can ensure the system will encounter droughts of appropriate severity.

2. The use of multiple replicates of input data ensures that the solutions are not dependent on any particular sequence of future climate and demand. This allows the use of a simulation model that can respond to changes in both infrastructure and operating rules. In turn, this enables both operating rules and infrastructure investments to be jointly optimized. The findings of *Mortazavi et al*. [2012] suggest that such capability is likely to produce significant benefits.

3. The potential equity issue arising from temporal discounting of social costs can be addressed in a multiobjective context by exploring the trade-offs between economic and equity criteria.

In the subsequent sections, the benefits of this formulation will be investigated using a case study.

2.2. Optimization Methods

This section briefly reviews the optimization methods that have been employed in capacity expansion problems and identifies those best suited for solving the problem described in section 2.1.

Approaches using some form of linear programming include *Khaliquzzaman and Subhash* [1997] who used network linear programming for sizing of reservoirs in a water resource system and *Mousavi and Ramamurthy* [2000] who integrated an optimal control theory approach with successive linear programming to determine the reservoir sizing. However, our formulation is not amenable to linear programming approaches because of nonlinearities in objective functions and constraints.

Dynamic programming (DP) [*Bellman*, 1957] has been used in the sizing and sequencing water resources projects [*Butcher et al*., 1969; *Erlenkotter*, 1973; *Erlenkotter and Trippi*, 1976; *Grossman and Marks*, 1977; *Knudsen and Rosbjerg*, 1977; *Morin and Esogbue*, 1971]. The main drawback of DP is that it can only be used for a relatively small number of projects because the number of possible states grows exponentially with the number of projects [*Luss*, 1982]. This so-called curse of dimensionality limits the application of DP [*Hsu et al*., 2008].

Evolutionary methods such as genetic algorithms (GAs), when carefully applied, are capable of handling complex systems and their associated nonlinearities with reasonable success. *Connarty and Dandy* [1996] applied a GA to a water supply system to find optimum water price and project sequences. In a similar way, *Chang et al*. [2009] hybridized a GA and constrained differential dynamic programming (CDDP) to optimize capacity expansion schedules for groundwater supply. They used a GA to investigate capacity expansion alternatives and then applied the CDDP algorithm to compute the optimal pumping policy associated with the selected expansion options. It is worth noting that this hierarchical optimization approach is likely to produce a suboptimal solution because the pumping policy and capacity expansion were not jointly optimized.

All of the above mentioned studies have only dealt with a single objective. *Rubinstein and Ortolano* [1984] used DP in multiobjective capacity expansion. Because DP cannot optimize two objectives jointly, they weighted the multiple objectives to form a single objective. *Yang et al*. [2007] used a hierarchical approach to integrate a multiobjective genetic algorithm (MOGA) with CDDP; MOGA was used to generate various combinations of reservoir capacity and CDDP was used to distribute optimal releases among reservoirs to satisfy water demand to the extent possible.

Of the general approaches reviewed, those based on evolutionary methods appear best suited for the multiobjective problem described in the previous section. They can interface with complex nonlinear simulation models, and handle multiple nonlinear objectives and constraints. In view of the satisfactory performance of the ε-dominance multiobjective optimization evolutionary algorithm (εMOEA) in *Mortazavi et al*. [2012], it was decided to use εMOEA to solve the multiobjective scheduling capacity expansion problem in the case study. εMOEA is a member of the evolutionary algorithm family whose distinguishing feature is the use of the ε-dominance concept which divides the objective space into hyperboxes of size ε and allows only one nondominated solution to reside in each box [*Laumanns et al*., 2002]. Other ε-dominance multiobjective evolutionary algorithms used in water resource applications such as ε-NSGA and BORG are discussed by *Reed et al*. [2013]. The practical advantage of this feature is that, by selecting an appropriate ε value for each objective, it is possible to avoid searching for solutions close to already found solutions.

3. Case Study: Description and Problem Formulation

This section introduces the case study which is based on the water supply headworks system for Canberra, Australia's capital city. An overview of the Canberra system is presented followed by a detailed formulation of the multiobjective scheduling capacity expansion problem.

3.1. Description of Canberra System

The Canberra headworks system serves a current population of approximately 420,000. Water is harvested from two catchments, Cotter and Googong, which flank the city to the west and east, respectively. A network of pipelines, pumping stations, and treatment plants connects four reservoirs to the Canberra demand zone. Releases from the reservoirs have to meet, not only the consumption needs of the Canberra urban area, but also environmental flow requirements.

A WATHNET5 [*Kuczera et al*., 2009] model of the Canberra system was constructed. Figure 2 presents the WATHNET5 schematic. The network of reservoirs, pumping stations, and water treatment plants supplies water to the demand zone labeled "Canberra." The existing system includes four reservoirs, Corin, Bendora, Cotter, and Googong. The reservoirs have a total storage capacity of 206,732 ML. Googong Reservoir is the largest reservoir in the system with a capacity of 121,084 ML. There are two water treatment plants, Googong and Stromlo WTP, serving the Canberra population.

In this case study, a hypothetical population scenario corresponding to a highly stressed system is presented. The base population is 175% of the current population and is assumed to grow at 1.2% per annum over a 30 year planning period with constant per-capita demand set at 178 kL/person/yr. It is noted that this arrangement ignores the correlation between demand and climate and thus may underestimate the

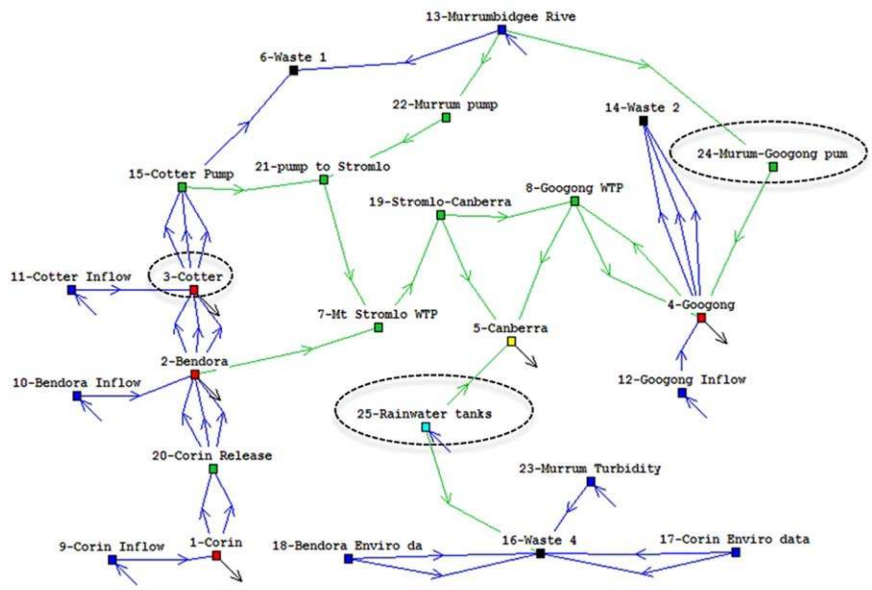

Figure 2. WATHNET5 schematic of Canberra headworks system.

consequences of drought. Multiple replicates of monthly future streamflow data for the 30 year planning period were sampled from a stochastic model calibrated to the historical record from 1871 to 2009.

To cater for the increase in demand, three options are available for augmenting supply—these are highlighted in the WATHNET5 schematic by dashed ovals. The first is to increase the capacity of Cotter Reservoir by up to 100,000 ML. The second is to build a new pump station to divert up to 6000 ML/month from the Murrumbidgee River into Googong Reservoir. The third option is to install domestic rainwater tanks in up to 15,000 houses.

Water consumption exhibits strong seasonality with peak monthly summer demand typically more than doubling monthly winter base demand. The increase in summer demand is largely due to outdoor water use associated with private and public irrigation of gardens and parks. As a result, there is considerable scope in targeting restrictions on outdoor water use. In this study, four levels of restrictions are available with Table 1 presenting the ratio of restricted to unrestricted demand for each level—the fourth level of restrictions corresponds to a total ban on outdoor water use.

3.2. Decision Variables

The 30 year planning horizon, nominally taken from 2010 to 2039, was divided into three equal-length planning stages with change points occurring in 2010, 2020, and 2030. Six decisions associated with operational and capacity expansion options are considered at each change point. These decisions and their lower and upper limits are presented in Table 2. We note that it is likely to be beneficial to allow operational decisions to be revisited more frequently than capacity expansion options.

Three decisions involve capacity expansion, namely Cotter Reservoir capacity, Murrumbidgee diversion capacity and the number of installed domestic rainwater tanks. The Murrumbidgee pump storage trigger controls the pumping of water from the Murrumbidgee River to Googong Reservoir after the Murrumbidgee diversion pump station is commissioned; when the storage fraction in Googong Reservoir falls below the trigger level, pumping from the Murrumbidgee River up to the maximum capacity of the pump station is initiated. The level-one restriction trigger x^2 and increment x^3 are operational decisions that regulate the occurrence of restrictions

Table 1. Demand Fractions for Each Restriction Level

Restriction Level	Ratio of Restricted to Unrestricted Demand
1	0.95
2	0.80
3	0.70
4	0.65

Table 2. List of Decision Variables

Decision	Description	Lower Limit	Upper Limit	Category
1	Cotter capacity upgrade (ML)	0	100,000	"One-off" capacity expansion
2	Level-one restriction storage trigger	0	1	Operational
3	Restriction storage trigger increment	0.05	0.25	Operational
4	Murrumbidgee diversion (ML/month)	0	6000	"One-off" capacity expansion
5	Murrumbidgee pump storage trigger	0	1	Operational
6	Number of houses with tanks	0	15,000	"Developing" capacity expansion

on consumption during a drought drawdown. If the total storage fraction falls below x^2 then the first restriction level is imposed. If the total storage fraction falls below x^2+x^3, then the second level of restrictions is imposed and so on.

3.3. Constraints

The decisions in a scheduling expansion problem may be constrained across planning stages. For example, decisions may be subject to a "one-off" constraint. If a nonzero value is assigned at a planning stage, then that value remains unchanged for all remaining planning stages. For example, if the capacity of Cotter is increased by 50,000 ML at the start of stage 2, then the capacity cannot be changed in subsequent planning periods.

Likewise decisions may be subject to a "developing" constraint where the decision value cannot decrease at subsequent planning stages. For example, the number of installed domestic rainwater tanks can be increased but not decreased at each planning stage. The following equation formalizes these constraints:

$$\begin{aligned} x^i_{t+1} = x^i_t \text{ if } x^i_t > 0 \text{ and } x^i \in \text{"one-off" constraints} \\ x^i_{t+1} \geq x^i_t \text{ if } x^i \in \text{"developing" constraints} \end{aligned} \tag{2}$$

where x^i_t is the *i*th decision at planning stage *t*.

There are a number of ways of handling such constraints when using evolutionary algorithms [*Michalewicz*, 1995]. In this study, a "repair infeasible solution" approach was used to implement equation (2). This involved using a script (or user-defined program) that is executed at each time step prior to the simulation. If a decision at a particular planning stage is infeasible, the script "repairs" it; the repaired feasible solution is not used to update the population. As noted, there are other ways of implementing such constraints. For example, the "one-off" constraint could be implemented with two decision variables, the first defining which stage (if any) the decision is invoked and the second defining the magnitude of the decision. This has the advantage of guaranteeing feasibility and reducing the size of the decision space when there are three or more planning stages.

3.4. Objective Functions

All the reviewed studies dealing with capacity expansion have sought to minimize the present worth of capital, operating and other costs. In the context of the formulation described in section 2.1, the expected value of the total present worth cost can be expressed as:

$$f(x) = \frac{1}{N}\sum_{t=1}^{T}\frac{1}{(1+r_o)^t}\sum_{r=1}^{N} C^r_t(x_{1:t}) + CR^r_t(x_{1:t}) + U^r_t(x_{1:t}) \tag{3}$$

where r_o is the discount rate and $C^r_t(x_{1:t})$ is the cost of infrastructure investments and operating costs for year *t* and replicate *r*, $CR^r_t(x_{1:t})$ is the economic cost of imposing restrictions on demand, and $U^r_t(x_{1:t})$ is the cost of unplanned demand shortfalls. As noted, exclusive reliance on this type of objective can hide the trade-off between capital and operating costs and the social costs arising from restrictions and unplanned shortfalls.

To explore this trade-off, two multiobjective formulations are considered:

1. Two-Objective Trade-Off

The expected value of the total present worth cost can be decomposed into its constituent costs to enable exploration of the trade-off between capital, operating, and unplanned shortfall costs and costs due to restrictions. This yields the following two objective functions:

$$\min_x f_1(x)=\frac{1}{N}\sum_{t=1}^{T}\frac{1}{(1+r_o)^t}\sum_{r=1}^{N}C_t^r(x_{1:t})+U_t^r(x_{1:t}) \tag{4}$$

$$\min_x f_2(x)=\frac{1}{N}\sum_{t=1}^{T}\frac{1}{(1+r_o)^t}\sum_{r=1}^{N}CR_t^r(x_{1:t}) \tag{5}$$

The second objective minimizes the expected discounted cost of imposing restrictions. However, minimizing discounted restriction costs can produce undesirable social outcomes. Due to discounting, the same frequency and severity of restrictions in the future will be being costed less than if the same were to occur in the present. As a result, minimization of discounted restriction costs can lead to a higher frequency and severity of restrictions in the future, a situation that often would be deemed politically unacceptable on social equity grounds.

2. Three-Objective Trade-Off

One way to overcome this practically significant shortcoming is to avoid discounting restriction costs. However, this in itself will not assure equity (or equal sharing of the burden of restrictions) over planning stages. To achieve this, it is necessary to introduce a third objective which seeks to minimize the difference in undiscounted restriction costs over the planning stages. These considerations lead to the following three objective functions:

$$\min_x f_1(x)=\frac{1}{N}\sum_{t=1}^{T}\frac{1}{(1+r_o)^t}\sum_{r=1}^{N}C_t^r(x_{1:t})+U_t^r(x_{1:t}) \tag{6}$$

$$\min_x f_2(x)=\frac{1}{M}\sum_{i=1}^{M}\frac{1}{N}\sum_{r=1}^{N}\sum_{t=T_i}^{t=T_{i+1}}CR_t^r(x_{1:t}) \tag{7}$$

$$\min_x f_3(x)=\sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(\frac{1}{N}\sum_{r=1}^{N}\sum_{t=T_i}^{t=T_{i+1}}CR_t^r(x_{1:t})-f_2(x)\right)^2} \tag{8}$$

The first objective seeks to minimize the present worth of capital, operating, and unplanned shortfall costs. The second minimizes the expected cost of undiscounted restrictions in a planning stage. The third minimizes the standard deviation of undiscounted restriction costs between planning stages. This effectively seeks to ensure the burden of restrictions on the community is shared as fairly as is possible across all planning stages. This approach is similar to that used by *Cai et al*. [2002] who used a similar dispersion measure as an indicator of temporal equity.

Instead of using the objectives (7) and (8), one could impose an equity constraint such that $f_3(x) \leq \alpha f_2(x)$. There are two problems with this approach. First, if α is set too low, there may be no feasible solution. Second, as there is no obvious choice for α, one would explore solutions for different values of α. In that case, it seems preferable to directly minimize the three objectives (6), (7), and (8) and explore the trade-offs.

The capital cost of the infrastructure options is summarized in Table 3. These costs are indicative and therefore should not be used outside this study. Two capital items involve a binary choice: if the item is selected by the optimizer, then there is a fixed setup cost along with a unit cost; if the item is not selected, there is zero capital cost. Operating costs include pumping and treatment costs for transfers from Cotter Reservoir, from the Murrumbidgee River, from Bendora Reservoir to Stromlo water treatment plant, from the Murrumbidgee River to Googong Reservoir, and from Stromlo water treatment plant to Googong Reservoir—the costs range from $23/ML to $250/ML.

Table 3. Infrastructure Cost of Capacity Expansion Decisions for Canberra Water Headworks System

Decision Variable	Unit Cost
Cotter Reservoir capacity upgrade	$\$50 \times 10^6 + \$1923$/ML
Murrumbidgee diversion	$\$20 \times 10^6 + \$42623$/ML
Rainwater tanks	\$3000/house

The unplanned shortfall cost was set to \$1.0 $\times$ 10^9/ML to ensure the optimizer steered away from solutions that resulted in "running out of water."

The estimation of the economic cost of restrictions follows the method of *Dandy* [1992]. Recognizing that restrictions in Australian urban areas are mainly targeted at outdoor water use, *Dandy* [1992] assumed that:

1. All the households have the same price elasticity of demand for outdoor use.

2. The price elasticity for outdoor use is constant within the range considered.

3. All households reduce their outdoor consumption in the same proportion in response to water restrictions.

and used a willingness-to-pay analysis to show that the economic cost of restrictions in a drought event could be approximated by

$$CR = \frac{\varepsilon}{1+\varepsilon} PQ\left[1-(1-R)^{\frac{1+\varepsilon}{\varepsilon}}\right] \; (if\, \varepsilon \neq -1) \tag{9}$$

where *CR* is the economic cost due to imposition of restrictions, *P* is the current price of water, *Q* is the unrestricted outdoor consumption, *R* is the fraction by which consumption is reduced, and ε is the price elasticity of demand for outdoor water. In this study, ε and *P* were set equal to -0.25 (which represents a relatively inelastic price response at the low end of empirical estimates) and \$600/ML, respectively.

4. Case Study Scenarios and Results

This section presents the main findings of the case study. Seven scenarios are investigated with the intent of demonstrating in a structured manner the limitations of earlier applications and the performance of the formulation described in section 2.1.

4.1. Description of Scenarios

Table 4 summarizes the seven scenarios used to demonstrate the benefits of applying the multiobjective formulation of section 2.1 to scheduling capacity expansion problems. The scenarios differ in the number of objectives, staging of infrastructure and operational decisions, the discount rate, and the initial volume of the reservoirs.

We devised five cases as summarized in Table 5. Each case used a number of scenarios for a particular purpose. Case 1 compares Scenarios 1 and 3 to explore the benefit of scheduling infrastructural and operational decisions jointly. Case 2 compares Scenarios 2–4 to assess the sensitivity of results to choice of discount rate. Thus far, only one objective is used in the optimization. Case 3 compares Scenarios 3 and 5 to demonstrate the additional insights arising from use of multiobjective optimization. Case 4 pursues this further comparing Scenarios 5 and 6 to investigate the trade-offs between equity and economic efficiency. Finally, Case 5 compares Scenarios 6 and 7 to demonstrate the sensitivity of solutions to initial conditions.

Table 4. List of Scenarios

Scenario	Number of Objectives (Relevant Equations)	Timing of Decisions: Infrastructural	Timing of Decisions: Operational	Discount Rate (%)	Initial Reservoir Volume
1	1 (3)	Stage 1	Any stage	5	Full
2	1 (3)	Any stage	Any stage	1	Full
3	1 (3)	Any stage	Any stage	5	Full
4	1 (3)	Any stage	Any stage	10	Full
5	2 (4 and 5)	Any stage	Any stage	5	Full
6	3 (6–8)	Any stage	Any stage	5	Full
7	3 (6–8)	Any stage	Any stage	5	10th percentile

Table 5. List of Case Studies and Their Associated Scenarios

Case	Scenarios	Purpose
1	1 and 3	Impact of using fixed or flexible operational rules
2	2–4	Sensitivity to choice of discount rate
3	3 and 5	Use multiple objectives to explore potential trade-off
4	5 and 6	Use multiple objectives to deal with equity issues
5	6 and 7	Sensitivity to initial reservoir volumes

In the first six scenarios, the reservoirs are assumed to be full at the start of the first planning stage. In Scenario 7, the initial storage in the reservoirs is set to the historic 10th percentile volume.

For each scenario, the simulations were conducted using 50 replicates of stochastically generated streamflow. It is acknowledged that more replicates would be needed to ensure a high level of drought security. However, a reduced number of replicates was chosen to make the computation on a desktop computer manageable for the seven scenarios. As *Mortazavi et al*. [2012] have already demonstrated the sensitivity of optimal solutions to the choice of maximum drought return period encountered in the simulation, it suffices in this study to demonstrate that the formulation is capable of dealing with any nominated maximum drought return period.

εMOEA is a probabilistic optimization method. Therefore, it is unable to guarantee convergence to the Pareto front. Accordingly, to reduce the chance of premature convergence affecting the results, each scenario was optimized 10 times with different random number seeds. The results presented are the nondominated solutions obtained from the pooled set of 10 runs. We consider this a conservative approach to help ensure our solutions are practically Pareto optimal. The εMOEA parameters were: probability of crossover = 1, probability of mutation = 0.01, and probability of inversion = 0.005. The maximum number of iterations for the single objective scenarios, 1–4, was set equal to 10,000, while for the multiple-objective scenarios, 5–7, it was set to 30,000. The εMOEA epsilon was set to 100,000 for the single objective cases and to 10,000 for the first objective and to 1000 for the second and third objectives in the multiobjective optimization. These epsilon values were deliberately chosen to be small to ensure high resolution. We note that in practice larger epsilon values would be used—apart from decreasing computational time, coarser resolution of the Pareto front reduces the chance of overwhelming decision makers without any practical loss of information [*Kollat and Reed*, 2007].

5. Results and Discussion

5.1. Case 1—Scenarios 1 and 3: Benefits of Flexible Operating Rules

This Case investigates the benefit of allowing operating rules to change across planning stages. It was noted in the literature review that infrastructure and operational decisions are not typically jointly optimized. In Scenario 1, all infrastructure decisions are made at start of the first planning stage, while operational decisions are flexible in the sense they can be revised at each planning stage. In contrast, in Scenario 3, all decisions can be revised at any planning stage subject to the staging constraints listed in Table 2.

Tables 6 and 7 present, respectively, the costs and decisions for the two scenarios. To provide a better understanding of how these scenarios deal with restrictions, the undiscounted restriction cost is presented for each planning stage in Table 6. Scenario 1 has the higher restriction cost indicating a greater reliance on imposing restrictions. In Scenario 1, the Murrumbidgee diversion had to be selected in the first stage. As a result, the stage-one restriction levels were set to a very low level. However, in stage two, a severe restriction policy was adopted with the level-one restriction trigger equal to 0.831. In contrast, Scenario 3 sees the Murrumbidgee diversion deferred to stage two with a capacity of 4221 ML/month, which is 75% greater than the capacity selected in Scenario 1. As a result of this increase in diversion capacity, the Scenario 3 level-one restriction trigger was set to 0.627 resulting in a lower chance of restrictions than in Scenario 1.

Table 6. Case 1 Results for Scenarios 1 and 3

Scenario	Total Present Worth Cost ($million)	Present Worth of Capital and Operational Cost ($million)	Total Present Worth of Restrictions Cost ($million)	Undiscounted Restriction Cost ($million)			Average of Undiscounted Restriction Cost Over Three Stages ($million)	Standard Deviation of Undiscounted Restriction Costs Over Three Stages ($million)
				Stage 1	Stage 2	Stage 3		
1	445	391	54	0	59.4	89.6	49.6	50.5
3	444	396	48	0.056	34.4	53.2	35.9	36.9

Table 7. Case 1 Optimum Decisions for Scenarios 1 and 3

	Scenario 1			Scenario 3		
	Planning Stage			Planning Stage		
Decisions	One	Two	Three	One	Two	Three
Cotter capacity upgrade (ML)	0	Same as stage one	Same as stage one	0	0	0
Level-one restriction storage trigger	0.019	0.831	0.627	0.4	0.627	0.752
Restriction storage trigger increment	0.224	0.149	0.063	0.096	0.055	0.149
Murrumbidgee diversion (ML/month)	2414	Same as stage one	Same as stage one	0	4221	4221
Murrumbidgee pump storage trigger	1	1	1	–	1	1
Number of houses with tanks	0	Same as stage one	Same as stage one	0	0	0

In both scenarios, the restriction cost increases with stage. Of particular note is that there were virtually no restrictions in stage one. This is because the system experienced the lowest demand and benefited most from the full state of the reservoirs at the start of the planning period. As a result, a low level-one restriction trigger was adopted at stage one. In the subsequent stages, the trigger was increased to cope with the growing demand and the decreasing influence of the initially full system. Of interest is the finding for both scenarios that the Cotter reservoir upgrade was not selected.

The most significant result is the small difference between the total present worth costs for the two scenarios. Scenario 1 has a capital/operating present worth cost (PWC) that is \$5 million less than that for Scenario 3. However, the restriction present worth cost for Scenario 3 is \$6 million less than for Scenario 1. As a result, Scenario 3 produces a total PWC that is \$1 million less than for Scenario 1. This highlights the value of revising operational decisions during each planning stage. Even though in Scenario 1, infrastructure decisions had to be made in stage one, the flexibility offered by revising operational decisions at each stage virtually compensated for the loss of flexibility in infrastructure decision making.

So while the optimal strategy is to provide flexibility in timing and sizing for both infrastructure and operational decisions, this Case illustrates the importance of flexibility in operational decisions.

5.2. Case 2—Scenarios 2–4: Sensitivity to Discount Rate

Luss [1982] noted that the estimation of discount rate is subjective. To investigate the effect of discount rate on the optimum solution, three scenarios with different discount rates, i.e., 1%, 5%, and 10% are compared. The total present worth costs are presented in Table 8. There are large differences in total PWC across the scenarios due to the spread in discount rates. The total PWC of Scenario 2 is about 3 times greater than for Scenario 4. However, the important point here is that the discount rate exerts considerable influence on the severity and frequency of restrictions over the three stages. As shown in Table 8, Scenarios 3 and 4 have very similar total discounted restriction costs but their average undiscounted restriction costs over the three stages are vastly different. It is also evident that the higher the discount rate, the higher the undiscounted restriction costs in later planning stages.

The optimum decisions for the three scenarios are presented in Table 9. It is noted that only in Scenario 2 is the Cotter upgrade option invoked with an upgrade capacity of 14,000 ML. This occurs because the use of the low discount rate of 1% would result in a blowout of restriction costs if additional storage were not available to reduce the frequency of restrictions.

The overall conclusion is that the discount rate determines how much reliance the optimizer places on the imposition of restrictions to avoid unplanned shortfalls and on how restrictions are distributed over the planning stages. Comparison of Scenarios 2–4 clearly shows that as the discount rate increases, the investment in infrastructure decreases at the expense of more restrictions imposed in future stages.

Table 8. Case 2 Comparison of Three Scenarios With Different Discount Rates

Total Present Worth Cost (\$million)	Capital and Operational Cost (\$million)	Total Present Worth of Restrictions Cost (\$million)	Undiscounted Restriction Cost (\$million)			Average of Undiscounted Restriction Cost Over Three Stages (\$million)	Standard Deviation of Restriction Costs Over Three Stages (\$million)
			Stage 1	Stage 2	Stage 3		
775	708	67	0	33.3	48.8	27.4	28.6
444	396	48	0.056	34.4	53.2	35.9	36.9
267	221	46	45.66	50.3	80.5	58.8	53.4

Table 9. Case 2 Optimum Decisions for Scenarios 2–4

	Scenario 2 ($r = 1\%$)			Scenario 3 ($r = 5\%$)			Scenario 4 ($r = 10\%$)		
	Planning Stage			Planning Stage			Planning Stage		
Decisions	One	Two	Three	One	Two	Three	One	Two	Three
Cotter capacity upgrade(ML)	0	0	14,352	0	0	0	0	0	0
Level-one restriction storage trigger	0.004	0.815	0.752	0.4	0.627	0.752	0.8	0.68	0.647
Restriction storage trigger increment	0.18	0.162	0.162	0.096	0.055	0.149	0.211	0.061	0.061
Murrumbidgee diversion (ML/month)	3995	3995	3995	0	4221	4221	0	3091	3091
Murrumbidgee pump storage trigger	1	1	1	–	1	1	–	1	1
Number of houses with tanks	0	0	0	0	0	0	0	0	0

5.3. Case 3—Scenarios 3 and 5: Revealing Trade-Offs

In the scenarios considered so far, only one objective, namely minimization of the total present worth cost, was considered. This cost includes capital, operating, and restriction costs—unplanned shortfall costs were always zero because of their punitive unit value. However, there is a trade-off between capital, operating, and unplanned shortfall costs and restriction costs. Indeed, more investment in infrastructure results in less need to impose restrictions and vice versa. To demonstrate this trade-off, Scenario 5 considers a multiobjective optimization jointly minimizing capital, operating, and unplanned shortfall costs and minimizing restriction costs. The two objectives are described by equations (4) and (5). In Figure 3, the Pareto frontier for Scenario 5 is presented. The results for Scenario 3, which is a special case of Scenario 5, are also shown in this figure. As expected, the Scenario 3 result is located on the Pareto frontier, which confirms that Scenario 3 represents only one of the possible solutions for Scenario 5.

Figure 3 shows there is a distinct trade-off between capital, operating, and unplanned shortfall costs and the cost of imposing restrictions. Indeed, the restriction cost can be very large in the absence of sufficient infrastructure investment. The figure shows there is initially a very favorable trade-off between higher capital investment and reduced restriction cost (see labeled points 1 and 2) followed by a progressively worsening trade-off culminating with virtually zero restriction costs when the present worth of capital, operating, and unplanned shortfall costs exceeds \$750 million. Up to \$750 million, there are no unplanned shortfall costs. However, beyond that, unplanned shortfall costs grow rapidly to produce minute reductions in restriction costs.

Discounting can hide the significance of the impact of restrictions on the community. To highlight this, the four solutions on the Pareto frontier in Figure 3 are summarized in Table 10. The results show that for all the solutions, progressively more severe restrictions are imposed in future planning stages highlighting the implicit inequity associated with discounting.

5.4. Case 4—Scenarios 5 and 6: Revealing Equity Trade-Offs

To deal explicitly with the equity issue and to offer the opportunity to moderate differences across planning stages, the three-objective formulation described by equations (6–8) is considered in Scenario 6. The first objective minimizes total present worth of capital, operating, and unplanned shortfall costs, while the remaining two objectives introduce equity considerations. The second objective seeks to minimize the magnitude of undiscounted restriction costs across the stages while the third objective seeks to minimize the difference in undiscounted restriction costs between stages.

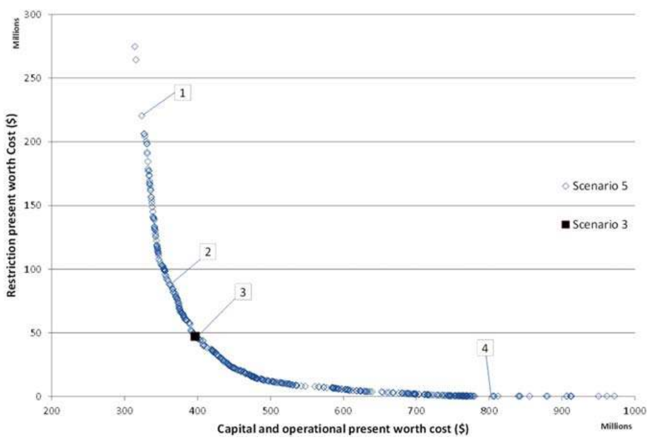

Figure 3. Pareto frontier for Scenario 5.

Figure 4 presents the Pareto frontier for Scenario 6. What is striking is the absence of a surface. The trade-offs essentially lie on a one-dimensional thread. Once significant restriction costs are encountered, there is a strong

Table 10. Comparison of Four Solutions Marked on the Pareto Frontier for Scenario 5 (Figure 3)

Present Worth of Capital and Operational Cost ($million)	Unplanned Shortfall Cost ($million)	Restrictions Present Worth Cost ($million)	Undiscounted Restriction Cost ($million)			Average of Undiscounted Restriction Cost Over Three Stages ($million)	Standard Deviation of Undiscounted Restriction Costs Over Three Stages ($million)
			Stage 1	Stage 2	Stage 3		
323	0	221	77.6	195.8	240.6	171	94.7
373	0	79.9	4.0	80.7	132.9	72.5	67.2
525	0	9.86	0	7.9	21.1	9.68	12.7
779	27.4	0.322	0	0	1.05	0.351	0.497

dependence between the average cost of undiscounted restrictions and the variability of cost across stages. To offer more insight into this trade-off, Figure 5 presents a projection of the three-dimensional Pareto front onto a two-dimensional objective plane with the third objective presented by different colors. It shows that the average of undiscounted restriction costs decreases substantially as capital, operating, and unplanned shortfall cost increases. It shows that, unless there is sufficient investment to eliminate restrictions, it is not possible to share equally the burden of restrictions across stages; moreover, as the average level of restriction costs in a stage grows there will be greater variability across the stages.

To highlight the difference between Scenarios 5 and 6, four solutions were selected for each scenario in order to have equal capital and operating costs for each pair of solutions. Table 11 presents the results. Comparison of restrictions present worth costs for Scenarios 5 and 6 indicate that Scenario 6 has lower restrictions present worth costs compared to Scenario 5. What is striking is the fact that Scenario 6 produces solutions with lower average (undiscounted) restriction costs across the planning stages and less variability in restriction cost between stages. This significantly improved equity outcome arises solely from the choice of objective functions. The use of three objectives enabled a more thorough exploration of cost and equity with the consequent identification of solutions with more equitable outcomes for the same capital and operating present worth cost.

Table 12 presents the decisions associated with the four Scenario 6 solutions in Table 11. The table ranks the solutions from smallest to highest capital and operating cost. The first solution has no capacity expansion except for the Murrumbidgee diversion in the second planning stage. The first and second stage level-one restriction triggers are very high indicating a high frequency of restrictions. In solutions 2 and 3, the size of the Murrumbidgee diversion increases. For solution 3, the Murrumbidgee diversion is brought forward to stage one and a rollout of rainwater tanks over the three stages is adopted with the number of

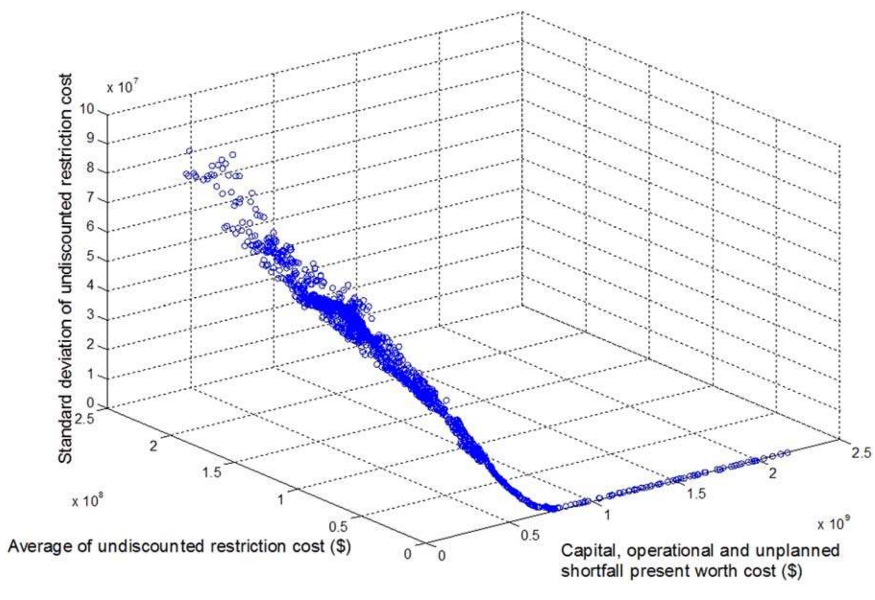

Figure 4. Pareto frontier for Scenario 6.

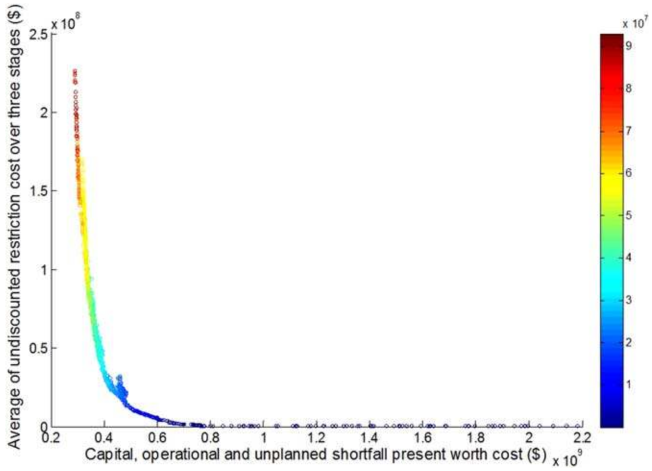

Figure 5. Pareto trade-off between present worth of capital, operational, and unplanned shortfall costs and average of undiscounted restriction costs over three planning stages for Scenario 6 with the color scale representing the standard deviation of undiscounted restriction cost.

tanks hitting the upper bound in stage two. Offsetting this increased capital investment are lower level-one restriction triggers leading to a lower frequency of restrictions. Solution 4 is the most costly with the Cotter upgrade and Murrumbidgee diversion maximized in stage one and rainwater tank installations maximized in stage two. The level-one restriction trigger is low resulting in virtual elimination of restrictions. It is noted that a very significant unplanned shortfall cost is required to bring about a minute reduction in restriction costs. As already noted, this is due to the punitive cost assigned to unplanned shortfalls. Of interest, all solutions opted for the Murrumbidgee diversion and set the pump trigger to one. This maximizes the yield from what is the most cost effective capital option.

5.5. Case 5—Scenarios 6 and 7: Sensitivity to Initial Conditions

In the previous cases, it was observed that in the first planning stage, restrictions were typically low. This is attributed to the fact that the system was full at the start of stage one and that stage one had the lowest demand. To separate the contributions of these two factors, Case 5 investigates the sensitivity of the Pareto-optimal solutions to the initial reservoir storage. In Scenario 6, the reservoirs were full at the start of the planning period, while in Scenario 7 the initial reservoir volumes were set equal to the 10th-percentile storage volumes (which were obtained from a 130 year simulation using historical flows and demand corresponding to the start of the planning period) —this corresponds to a total initial volume equal to about 38% of total reservoir capacity. Figures 6 and 7 show the Pareto frontiers for Scenarios 6 and 7. They clearly show that solutions for Scenario 7 are more expensive than for Scenario 6 especially as the restriction costs increase. We selected four solutions on each front which are marked on Figure 7. These solutions were selected to produce four pairs where each member of a pair was located on a different Pareto front but had a near equal average undiscounted restriction cost. Table 13 presents the three objective function values for each solution as well as the undiscounted restriction costs for each stage for Scenarios 6 and 7, respectively, whereas Table 14 presents the decisions associated with each marked solution for Scenarios 6 and 7, respectively.

The results show that the optimal scheduling policy is affected by the initial state of the storages. The lower initial storage in Scenario 7 makes the system more vulnerable to drought in the first planning stage. The stage-one decisions reflect this vulnerability by bringing forward to stage one the capital investments that were deferred to latter stages in Scenario 6. For example, for solution 1, the Murrumbidgee diversion is brought forward to stage one in Scenario 7 whereas in Scenario 6 it was deferred to stage two. Likewise, for solution 4 the rollout of over 14,000 rainwater tanks was brought forward from stage three in Scenario 6 to stage one in Scenario 7. Even though the initial storage corresponds to the historic 10th-percentile value in Scenario 7 (which corresponds to 38% storage), only solutions 1 and 2 commence with the system in restrictions.

5.6. Discussion

The use of multistage decisions allows the optimizer to identify solutions that would be classified as being “flexible” in the sense that the solutions can adapt to changing future circumstances. In this case study, the optimizer exploited the fact that at the beginning of all but one scenario, the system was full and subject to the lowest demand. As a consequence, the optimizer tended to defer augmentations to later stages and rely on adjusting operational decision variables. Even in this constrained case study, the benefit of flexibility

Table 11. Comparison of Four Solutions on the Pareto Frontiers for Scenarios 5 and 6

Solution Label	Scenario 5: Present Worth of Capital and Operational Cost ($million)	Scenario 5: Unplanned Shortfall Cost ($million)	Scenario 5: Restrictions Present Worth Cost ($million)	Scenario 5: Average of Undiscounted Restriction Cost Over Three Stages ($million)	Scenario 5: Standard Deviation of Undiscounted Restriction Costs Over Three Stages ($million)	Scenario 6: Present Worth of Capital and Operational Cost ($million)	Scenario 6: Unplanned Shortfall Cost ($million)	Scenario 6: Restrictions Present Worth Cost ($million)	Scenario 6: Average of Undiscounted Restriction Cost Over Three Stages ($million)	Scenario 6: Standard Deviation of Undiscounted Restriction Costs Over Three Stages ($million)
1	323	0	221	171	94.7	323	0	184	116	61
2	373	0	79.9	72.5	67.2	373	0	75.66	51.4	40.7
3	525	0	9.86	9.68	12.7	525	0	9.89	9.47	12.2
4	778.9	27.44	0.322	0.351	0.497	781.4	27.4	0.318	0.346	0.490

Table 12. Decisions Associated With the Four Solutions Presented in Table 10 for Scenario 6

Solution	Capital, Operational and Unplanned Shortfall Present Worth Cost ($m)	Stage 1: Cotter Capacity Expansion	Stage 1: First Restriction Trigger	Stage 1: Trigger Intervals	Stage 1: Murrumbidgee Diversion Capacity	Stage 1: Murrumbidgee Pump Trigger	Stage 1: Number of Houses With Tanks	Stage 2: Cotter Capacity Expansion	Stage 2: First Restriction Trigger	Stage 2: Trigger Intervals	Stage 2: Murrumbidgee Diversion Capacity	Stage 2: Murrumbidgee Pump Trigger	Stage 2: Number of Houses With Tanks	Stage 3: Cotter Capacity Expansion	Stage 3: First Restriction Trigger	Stage 3: Trigger Intervals	Stage 3: Murrumbidgee Diversion Capacity	Stage 3: Murrumbidgee Pump Trigger	Stage 3: Number of Houses With Tanks
1	323	0	0.996	0.140	0	-	0	0	0.929	0.143	1962	1	0	0	0.760	0.129	1962	1	0
2	373	0	0.827	0.239	0	-	0	0	0.752	0.0837	3402	1	0	0	0.564	0.0618	3402	1	0
3	525	0	0	0.195	5774	1	1256	0	0.564	0.097	5774	1	5932	0	0.568	0.119	5774	1	14,686
4	809	100,000	0.129	0.181	6000	1	2235	100,000	0	0.222	6000	1	15,000	100,000	0.301	0.0.119	6000	1	15,000

was evident with clearly superior outcomes over solutions which limited flexibility such as in scenario 1 where infrastructure decisions had to be selected at stage one.

The formulation developed in this case study uses multiple replicates of future inputs to the system—here an input is an exogenous variable that cannot be controlled by the system. The case study illustrated the multireplicate input approach using streamflow as the exogenous input. The key idea is to ensure that the optimizer is "aware" that future streamflow is highly variable. However, the methodology is more general in the sense that the set of inputs can be expanded to include multiple exogenous variables that are uncertain and cannot be controlled by the system—such variables may include population growth rates, social expectations, and so on. As more of such variables are internalized into the optimization, one would expect solutions to become more robust and practically useful. However, such generalization is not trivial and presents a range of significant problems which are well beyond the scope of this study.

The multiobjective scheduling capacity expansion formulation in section 2 was abstract. Only in the case study were specific objective functions, constraints and decisions proposed. This was done deliberately to stress that the problem formulation should be user driven and user relevant, rather than constrained by the limitations of the optimization method. The use of multiobjective evolutionary algorithms helps empower the decision maker to formulate the optimization problem so it is more closely aligned with his/her expectations. The WATHNET5 software was built on this premise—it is generic in the sense that a scripting language is used to define objectives, constraints, and decisions. Nonetheless, there remain very significant challenges to overcome before the full complexity and uncertainty faced by decision makers can be embodied in optimization models.

The Canberra case study was conducted on a four-core desktop computer with typical run times of 16 h—this restricted the number of replicates to 50. However, because evolutionary algorithms are readily parallelized, access to a large cluster of CPU cores would enable use of many more replicates to ensure the optimizer "sees" more extreme droughts and application to more complex systems.

6. Conclusion

Various options are available to water agencies responsible for meeting the growing demand for water arising from urban population growth. These options include operational decisions such as imposing restrictions, rules controlling water transfers and allocations, policies promoting more efficient water use, and infrastructure investments such as harvesting new sources of water. Because the performance of the urban water resource system will change over time, the challenge is to find the best combination of these options over time.

Many studies have investigated methods to find the optimum size and timing of capacity expansion of projects with the aim of minimizing the total present worth cost. However, review of these studies identified a number of practically significant shortcomings. These include the following:

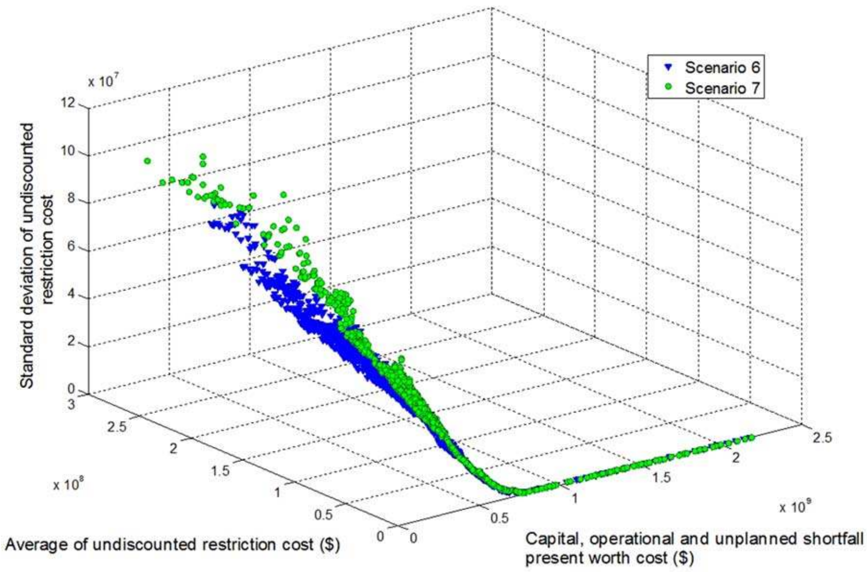

Figure 6. Comparison of Pareto frontiers for Scenarios 6 and 7.

1. Minimizing a single objective based on present worth cost hides a socially sensitive equity issue related to the sharing of the burden of restrictions across planning stages.

2. Failure to jointly optimize infrastructure and operational decisions.

3. Failure to address drought security adequately due to inadequate sampling of severe droughts.

This study presents a multiobjective formulation that addresses these shortcomings in a practicable manner. The formulation uses a multireplicate approach in which multiple realizations of future inputs are simulated. It permits use of a full simulation model that enables the tracking of system performance over time and enables the optimization algorithm to search for the best mix of both infrastructure and operational decisions.

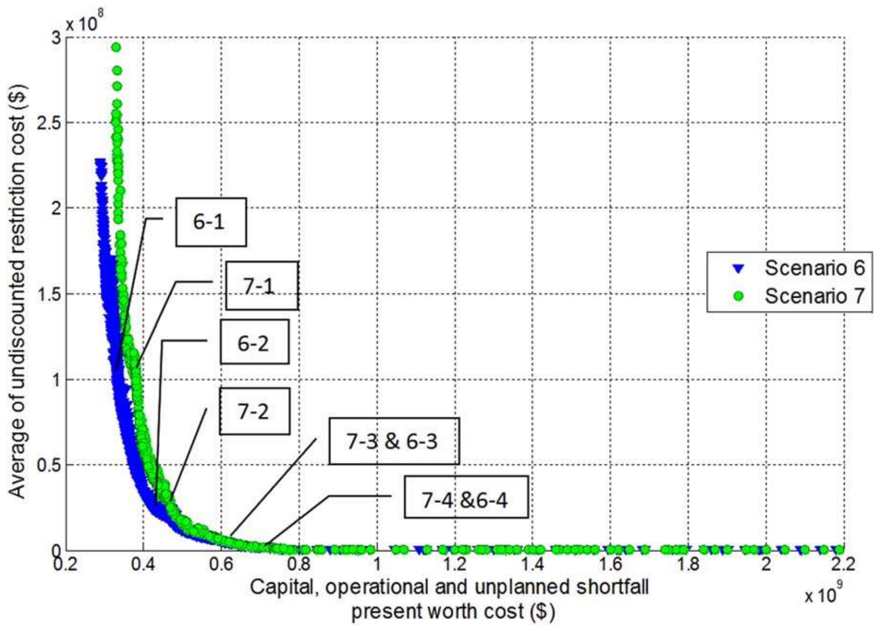

Figure 7. Pareto trade-off between present worth of capital, operational, and unplanned shortfall costs and average of undiscounted restriction costs over three planning stages for Scenarios 6 and 7 showing location of four selected solutions on each front.

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Table 13. Comparison of Four Points Marked on Figure 7 of Pareto Frontier for Scenarios 6 and 7

Scenario	Solution	Present Worth of Capital and Operational Cost ($million)	Unplanned Shortfall Cost ($million)	Undiscounted Restriction Cost ($million)			Average of Undiscounted Restriction Cost Over Three Stages ($million)	Standard Deviation Of Undiscounted Restriction Costs Over Three Stages ($million)
				Stage 1	Stage 2	Stage 3		
6	1	333.46	0	130.85	96.56	85.01	104.14	54.98
	2	454.93	0	10.33	31.83	33.65	25.26	21.87
	3	612.70	0	0.03	5.41	6.90	4.11	5.51
	4	679.29	0	0.00	3.75	1.34	1.69	2.39
7	1	379.9	0	136.64	57.92	117.76	104.11	61.6
	2	470	0	10.04	25.10	40.09	25.08	22.64
	3	630.09	0	0.50	5.98	5.85	4.11	5.38
	4	716.64	0	0.38	2.94	1.71	1.68	2.32

Table 14. Optimum Decisions for Four Solutions Presented in Table 13 for Scenarios 6 and 7

		Planning Stage 1						Planning Stage 2						Planning Stage 3					
Scenario	Solution	Cotter Capacity Expansion	First Restriction Trigger	Trigger Intervals	Murrumbidgee Diversion Capacity	Murrumbidgee Pump Trigger	Number of Houses With Tanks	Cotter Capacity Expansion	First Restriction Trigger	Trigger Intervals	Murrumbidgee Diversion Capacity	Murrumbidgee Pump Trigger	Number of Houses With Tanks	Cotter Capacity Expansion	First Restriction Trigger	Trigger Intervals	Murrumbidgee Diversion Capacity	Murrumbidgee Pump Trigger	Number of Houses With Tanks
6	1	0	1.000	0.169	0	0.216	0	0	0.937	0.150	2414	1	0	0	0.761	0.145	2414	1.000	0
	2	0	0.820	0.216	4391	1.000	0	0	0.882	0.234	4391	1	0	0	0.627	0.134	4391	1.000	0
	3	0	0.263	0.197	6000	1.000	486	52,000	0.522	0.123	6000	1	885	52,000	0.502	0.148	6000	1.000	4804
	4	0	0.004	0.223	6000	1.000	372	100,000	0.337	0.051	6000	1	896	100,000	0.298	0.099	6000	1.000	13,431
7	1	0	0.988	0.141	2414	1	0	0	0.839	0.149	2414	1	0	0	0.784	0.009	2414	1	0
	2	0	0.501	0.240	4221	1	286	0	0.764	0.148	4221	1	3648	0	0.721	0.173	4221	1	6372
	3	0	0.137	0.006	5350	1	0	84,000	0.505	0.119	5350	1	0	84,000	0.525	0.197	5350	1	0
	4	0	0	0.209	5971	1	14,804	100,000	0.352	0.007	5971	1	14,863	100,000	0.403	0.162	5971	1	14,921

A case study based on the Canberra headworks system demonstrated the capability of the formulation. The following conclusions, though derived from the case study, are deemed to have applicability beyond the case study itself:

1. Minimizing total present worth cost can lead to more severe and frequent restrictions in future planning stages. This is potentially an unacceptable social/political outcome. The magnitude of this inequity is dependent on the discount rate with higher discount rates leading to greater temporal inequity in restriction outcomes.

2. The use of a multiobjective formulation, which minimizes the present cost of capital, operating, and unplanned shortfall costs together with the level and variability of restriction costs across planning stages, makes the equity issue visible to a decision maker.

3. The optimal scheduling solution can be sensitive to the initial state of the system. This is by no means an undesirable finding. Indeed, by being able to schedule both infrastructure and operational decisions across multiple planning stages, it is possible to adapt to changing circumstances. This flexibility is arguably the most important feature of the formulation developed in this study.

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