How flexibility in urban water resource decisions helps to manage uncertainty?

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Abstract Uncertainty in future climate change and demand presents a significant challenge to the planning and management of urban water supply systems. One of the approaches to deal with uncertainty is to break large investments into a series of smaller decisions. In fact, spreading investments over time lets decision makers respond to unfolding contingences. This study considers the issue of identifying Pareto-optimal solutions for urban water supply that are robust in the face of uncertain future demand. The approach is based on the simulation of three plausible future demand scenarios to allow expected economic performance to be traded off against the variability in performance. A case study demonstrates the feasibility of this approach for a complex urban water supply system. The primary objective is to minimize the expected present worth of costs associated with infrastructure decisions, operating rules and drought contingency plans. By introducing a second objective which minimizes the difference in present worth costs across future demand scenarios, the trade-off between efficiency and robustness is identified. The results show that a significant change in investment and operating strategy occurs when the decision maker expresses a stronger preference for robustness.

Key words multi-objective optimization; demand growth; urban water management; scheduling

INTRODUCTION

The identification of solutions for urban water resource systems that are both optimal and robust in the presence of uncertainty presents a difficult challenge. In particular, decision makers need to deal with significant uncertainty about future climate (which affects supply) and anthropogenic forcing (which affects the demand placed on the system). Much of this uncertainty can be described using probability distributions that have been inferred from past data on system behaviour. However, some aspects of this uncertainty are not amenable to such statistical analysis. In such cases, while the future events are identifiable, there is insufficient data and prior knowledge to confidently assign probabilities to such events. In the context of urban water resource systems, one such uncertainty is future demand. Forecasting urban water demand over decadal time scales is subject to considerable uncertainty. This arises because there is considerable uncertainty in factors (such as climate change, population growth and long-term conservation strategies) that influence future demand (House-Peters & Chang, 2011). The issue of optimal decision making for urban water supply in the presence of future demand uncertainty is the focus of this study.

In the water resource field, Watkins & McKinney (1997) reviewed a considerable amount of literature on making decisions that hedge against risk. Watkins & McKinney (1997) presented a framework that formally incorporated risk aversion into the optimization problem, thus enabling trade-offs to be made between expected performance and robustness. They applied the robust optimization framework of Mulvey *et al.* (1995) to two water resource problems. By assigning probabilities to different scenarios defined as possible model parameters, they explored two types of robustness, optimality-robustness which identifies solutions that are “close” to optimal for all scenarios, and feasibility-robustness which identifies solutions that remain “almost” feasible for all scenarios. The principal limitation of the Watkins and McKinney approach was the restrictive nature of the classical mathematical program that simulated the water resource system and that defined the objectives. This limitation can be overcome using a multi-objective evolutionary algorithm to identify the Pareto optimal solution set (Deb, 2001; Mortazavi *et al.* 2012).

In this study, we use the WATHNET5 model (Kuczera *et al.*, 2009) to identify the Pareto optimal trade-offs between efficient performance and robustness in the face of uncertainty about future demand. The case study considers identifying the Pareto optimal schedules of staged decisions for a hypothetical future water supply scenario for Canberra, Australia’s capital city.

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DESCRIPTION OF CANBERRA WATER SUPPLY 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 consumptive needs of the Canberra urban area, but also environmental flow requirements defined in the water authority's operating license.

A WATHNET5 model of the Canberra system was constructed. Figure 1 presents the WATHNET5 schematic with the "R" nodes representing reservoirs, "S" stream nodes, "D" demand zones, and "W"/"S" waste/sink nodes. WATHNET5 (Kuczera *et al*., 2009) is an example of a generalized simulation model that uses a network linear program to simulate the operation of a wide range of water supply headworks configurations. Instead of using explicit rules to make water assignments, it uses information about the current state of the system as well as monthly forecasts of streamflow and demand to formulate a network linear program that determines water assignments.

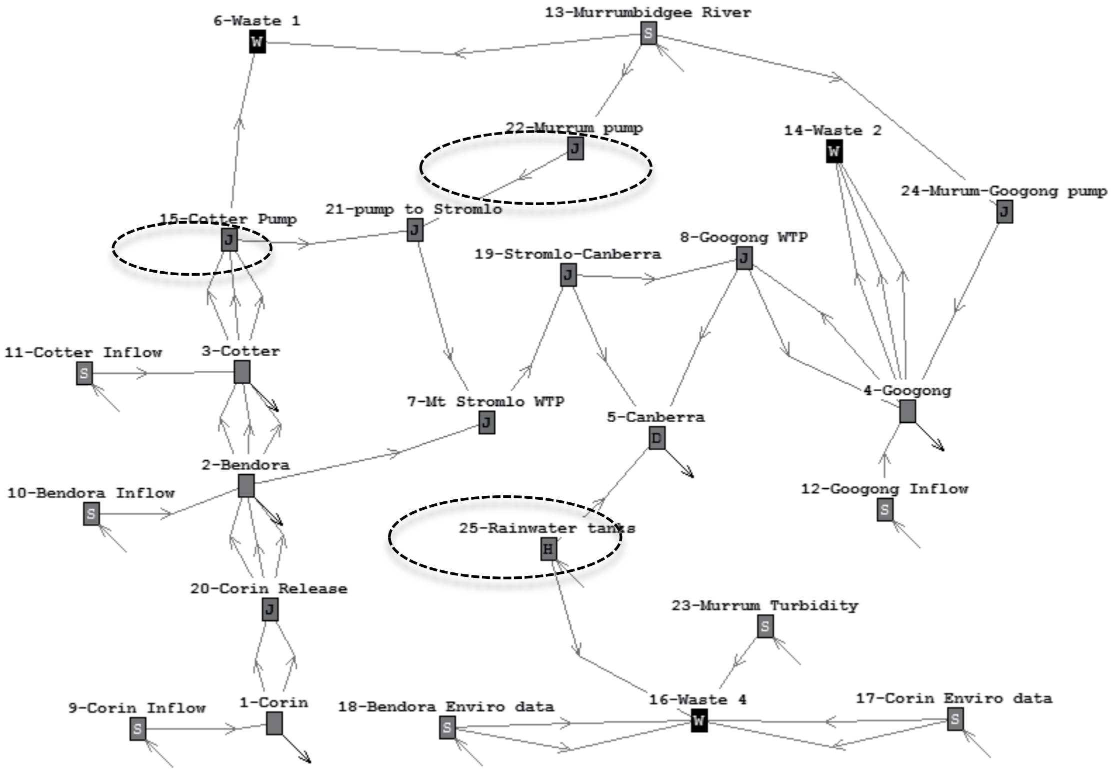

Fig. 1 WATHNET5 schematic of Canberra headworks system.

The network of reservoirs, pumping stations and water treatment plants supplies water to the demand zone labelled "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. For simplicity, the same demand time series was used in all replicates; it is noted that this arrangement ignores the correlation between demand and climate and thus may underestimate the consequences of drought.

Multiple replicates of monthly future streamflow data from 2010 to 2040 were sampled from a stochastic model calibrated to an historical record from 1871 to 2009.

To cater for the increase in demand arising from population growth, 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.

The high seasonality in water consumption due to summer outdoor water use indicates there is considerable scope for reducing demand by imposing 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.

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

FUTURE DEMAND SCENARIOS

As the primary purpose of this case study is to provide insight about robust optimization, a simple method for constructing future demand scenarios was adopted. A 30-year demand time series based on historical variability was constructed for the base population case, which represents 175% of the current population. Three demand scenarios were then developed by scaling the base series using annual growth rates of 1.05%, 1.2% and 2.0% over the 30-year planning period. Figure 2 presents the 30-year demand time series for three future demand scenarios. What is evident is the high seasonality of water consumption with outdoor water usage during the hot, dry summer months more than doubling winter consumption.

OPTIMIZATION OBJECTIVES AND DECISION VARIABLES

The common theme that emerges from review of robust optimization approaches is the need to explore the Pareto-optimal trade-off between measures of expected performance and sensitivity of the performance measures to future events or states. Our formulation of the robust optimization problem exploits the generality offered by evolutionary multi-criterion optimization algorithms.

The 30-year planning horizon, 2010 to 2040, was divided into three equal-length planning stages with change points occurring in 2010, 2020 and 2030. At the start of each planning stage, i = 1,2,3, a set of decisions are implemented. The notation x_i^j denotes the jth decision implemented at the start of the ith planning stage. In this study, six decisions associated with operational and capacity expansion options were considered at each change point. These decisions and their lower and upper limits are presented in Table 2.

Three decisions involve capacity expansion, namely the capacity of Cotter Reservoir, the 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 level 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 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, etc.

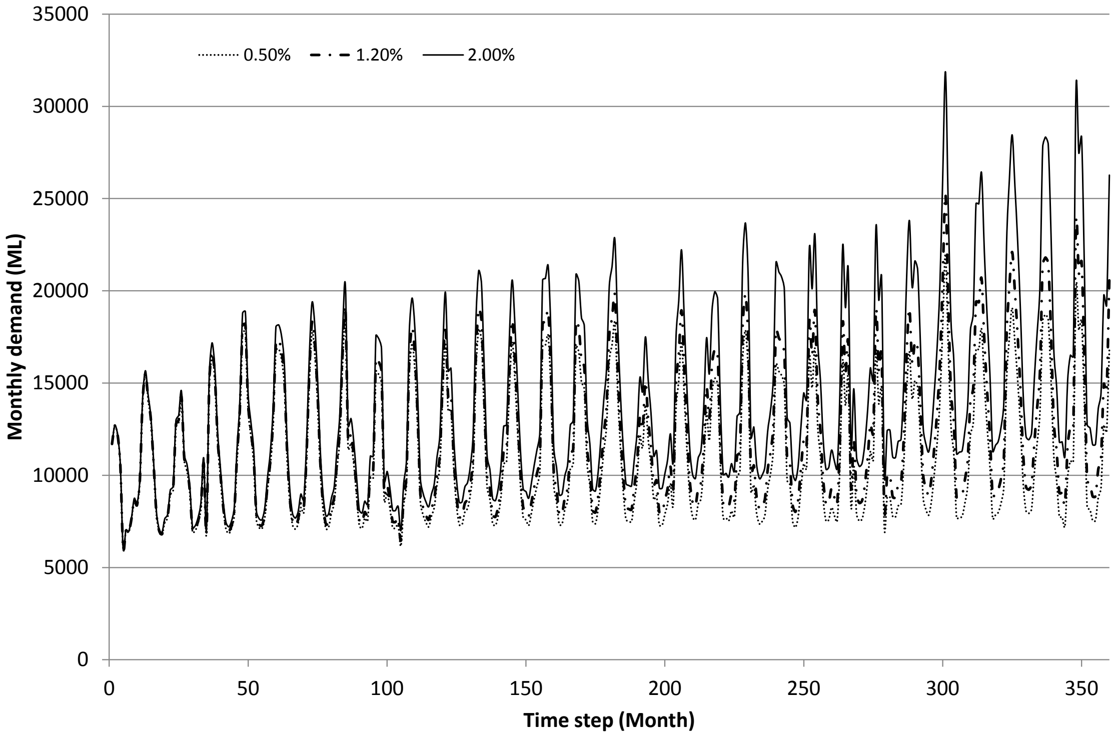

Fig. 2 Comparison of Canberra unrestricted demand time series for different annual growth rates.

Table 2 List of decision variables.

Decision	Description	Lower limit	Upper limit	Category
1	Cotter capacity upgrade(ML)	0	100 000	"Zero-one" 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	"Zero-one" capacity expansion
5	Murrumbidgee pump storage trigger	0	1	Operational
6	Number of houses with tanks	0	15 000	"Developing" capacity expansion

The scheduling expansion problem is typically constrained. For example, decisions may belong to the "zero-one" category. If a non-zero 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 it will remain unchanged for the remainder of the planning period. Another decision category imposing a constraint is the "developing" category. In this case, 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:

$$\begin{aligned} &x_{t+1}^{i} = x_{t}^{i} \text{ if } x_{t}^{i} > 0 \text{ and } x^{i} \in \text{"zero-one" decisions} \\ &x_{t+1}^{i} \geq x_{t}^{i} \text{ if } x^{i} \in \text{"developing" decisions} \end{aligned} \tag{1}$$

In this study, the principal optimization objective is to minimize the present worth of expected costs associated with infrastructure investment, system operation, and imposition of restrictions using a 5% discount rate. The total expected present worth cost can be expressed as:

$$f(x) = \frac{1}{N}\sum_{t=1}^{T}\frac{1}{(1+r_o)^t}\sum_{r=1}^{N} C_t^r(x_{1:t}) + CR_t^r(x_{1:t}) \tag{2}$$

where r_o is the discount rate and $C_t^r(x_{1:t})$ is the cost of infrastructure investments and operating costs for year t and replicate r, $CR_t^r(x_{1:t})$ is the economic cost of imposing restrictions on demand and $x_{1:t}$ denotes all the decisions made up to and including year t, T is the number of years in the planning period (30 years) and N is the number of replicates, set to 100 in this study.

A robustness measure expresses some measure of variability of present worth total cost across the different scenarios. For example, it may be the standard deviation of the present worth costs over the three scenarios. For more risk averse decision makers, measures based on worst case outcomes may be preferable such as the spread defined as the maximum range of the present worth cost over the three scenarios – such measures have the advantage of not relying on assigning uncertain probabilities to the future demand scenarios. In this study, the spread of the present worth cost of scenarios is adopted as the second objective.

The multi-objective optimization was conducted using the εMOEA evolutionary algorithm, proposed by Laumanns *et al.* (2002) and modified by Jefferson *et al.* (2005). εMOEA is one of many evolutionary optimization algorithms. It is based on the concept of ε-dominance which has been found to provide an efficient mechanism for maintaining diversity in multi-objective optimization problems without sacrificing rate of convergence to the Pareto-optimal front – see Laumanns *et al.* (2002) and Deb *et al.* (2003). εMOEA was parameterized according to the most commonly recommended settings from the literature (Deb *et al.*, 2003) and terminated after 20 000 evaluations.

RESULTS AND DISCUSSION

Figure 3 presents the approximate Pareto-optimal front showing the trade-off between expected present worth cost and cost spread. These results were obtained from five runs with different seed numbers. Solution 5 has the smallest cost spread over the demand scenarios but the highest present worth cost. It is noted that between solution 1 and 3 there is a reduction in cost spread $24 million for an increase of $137 million in total present worth cost. However, the trade-off becomes less favourable between solution 4 and 5 where a reduction in cost spread of less than $1 million requires an increase in present worth cost of $23 million. An analysis of the decisions corresponding to these solutions will help explain this change in trade-off characteristics.

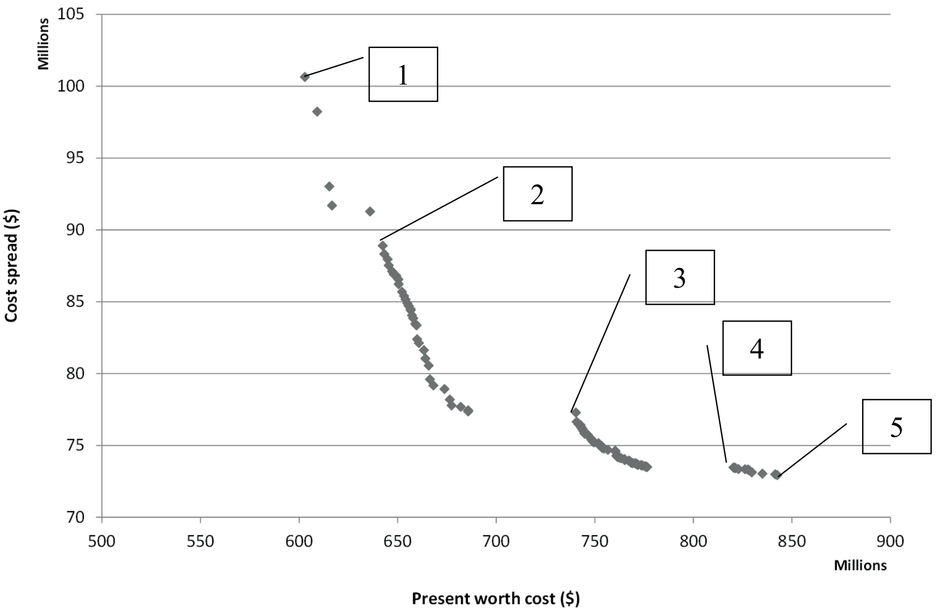

Fig. 3 Robust Pareto optimal solutions.

Common to all these solutions is the fact that the system did not run out of water in any of the demand scenarios. This is a consequence of the constraint applied on unplanned shortfalls. It ensures that all solutions under the worst case demand scenario can cope with the worst drought experienced in the 100 30-year stochastic replicates. Such an outcome is consistent with the practice of ensuring high level of drought security for urban water supply.

Table 3 summarizes the five solutions identified in Fig. 3. For solutions 1 and 2, Cotter capacity is equal to zero in the first planning stage while it is increased close to its maximum value in the second planning stage. The Murrumbidgee diversion capacity is relatively small in solutions 1 and 2, while it is set to its maximum value in other solutions. In solutions 3 to 5, Cotter capacity is set equal close to its maximum value at the first planning stage. The main difference between solution 3 and solutions 4 and 5 is the number of houses with rainwater tanks. In solution 5, the most expensive source option, namely installation of domestic rainwater tanks, was exploited close to its maximum. This was the only way to reduce the cost spread as the Cotter and Murrumbidgee options were already close to fully exploited. However, this strategy had limited impact on reducing the cost spread.

Table 3 Decisions associated with the five Pareto optimal solutions presented in Fig. 3.

			Planning stage 1						Planning stage 2						Planning stage 3					
Solution	Present Worth Cost ($m)	Cost Spread ($m)	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
1	603	101	0	0.349	0.121	5351	1.0	0	44000	0.753	0.099	5351	1.00	0	44000	0.816	0.118	5351	1.00	0
2	642	89	0	0.357	0.146	5294	1.0	0	70353	0.753	0.149	5294	1.00	0	70353	0.690	0.106	5294	1.00	0
3	740	77	92000	0.004	0.237	5718	1.0	0	92000	0.667	0.099	5718	1.00	0	92000	0.627	0.103	5718	1.00	0
4	820	73	99529	0.004	0.237	6000	0.9	24	99529	0.635	0.099	6000	1.00	242	99529	0.627	0.118	6000	1.00	3863
5	843	73	99529	0.000	0.212	6000	0.9	1027	99529	0.635	0.099	6000	1.00	10481	99529	0.627	0.118	6000	1.00	14216

Table 4 Frequency of restrictions for five solutions labelled in Fig. 3.

Solution	Demand scenario	Frequency of restrictions %		
		Stage 1	Stage 2	Stage 3
1	1 (Growth =1.05%)	0.32	8.62	11.14
	2 (Growth =1.20%)	0.41	12.98	21.83
	3 (Growth =2.0%)	0.57	20.13	37.23
2	1 (Growth =1.05%)	0.33	10.25	2.58
	2 (Growth =1.20%)	0.45	14.16	8.93
	3 (Growth =2.0%)	0.64	21.10	22.23
3	1 (Growth =1.05%)	0.00	2.03	1.08
	2 (Growth =1.20%)	0.00	3.07	4.99
	3 (Growth =2.0%)	0.00	6.28	15.48
4	1 (Growth =1.05%)	0.00	1.48	1.00
	2 (Growth =1.20%)	0.00	2.51	4.45
	3 (Growth =2.0%)	0.00	4.78	14.74
5	1 (Growth =1.05%)	0.00	1.53	0.98
	2 (Growth =1.20%)	0.00	2.54	4.41
	3 (Growth =2.0%)	0.00	4.90	14.67

Interestingly, for all the solutions, the level-one restriction trigger is low in the first stage and jumps substantially in stage 2. This is a consequence of two factors, a full system at the start of the simulation in 2010 and the discounting of restriction costs (with restrictions occurring in the future having a smaller present worth cost than restrictions occurring in the present). Table 4 presents the frequency of restrictions in each planning stage for each demand scenario of the five solutions. There is a clear trend of increasing restriction frequency with increasing demand growth. In stages 2 and 3 the least robust solutions 1 and 2 see a large jump in restriction frequency peaking at 37%. In contrast for the more robust solutions 3, 4 and 5, the sensitivity of restriction frequency to demand scenario is subdued. That said, for the high growth scenario, the restriction frequency peaks at 15% which would border on being socially unacceptable. However, there is little opportunity to further reduce the frequency of restrictions – all the options that can reduce restriction frequency are at their upper bound for solution 5. A wider range of trade-offs is only possible if the decision space were to be expanded to increase the opportunities for source augmentation and/or demand substitution.

CONCLUSION

The difficult-to-quantify and possibly considerable uncertainty associated with future demand scenarios presents a significant challenge to the planning and management of urban water supply systems, which typically have to provide high levels of drought security and high levels of service. This study considered the issue of identifying optimal solutions that are robust in the face of uncertain future demand. The availability of evolutionary multi-objective optimization algorithms makes possible realistic implementation of robust multi-criterion optimization together with staging of decisions to maximize flexibility. The approach is based on the simulation of multiple plausible future demands to allow expected performance to be traded off against the variability in performance.

The case study based on the Canberra water supply system demonstrated the feasibility of this approach. The primary objective was to minimize the present worth of costs associated with infrastructure decisions, operation and restrictions. By introducing a second objective which minimized the difference in present worth costs across future demand scenarios, the trade-off between efficiency and robustness could be identified. The results showed that the more robust solutions favour a strategy that is less dependent on the use of restrictions to reduce domestic outdoor water use and more dependent on costly sources of water in the form of additional storage, inter-basin transfers and roofwater harvesting using domestic water tanks.

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