APPLICATION OF MULTI OBJECTIVE OPTIMIZATION FOR MANAGING URBAN DROUGHT SECURITY IN THE PRESENCE OF POPULATION GROWTH

MOHAMMAD MORTAZAVI (1), GEORGE KUCZERA (1), LIJIE CUI (1)
(1): Faculty of Engineering and Built Environment, University of Newcastle, University Drive, Callaghan, NSW, Australia

Scheduling expansion problems have typically been formulated to find the timing and scale of predefined projects that minimize the total present worth cost. The high capital and environmental costs of major infrastructure options have stimulated interest in optimizing operational decisions such as conservation rules as a way of delaying or avoiding investment in major infrastructure. This paper demonstrates the benefit of jointly optimizing staged infrastructure and operational decisions to cope with growth in urban water demand. It also demonstrates social equity problems that may arise from minimizing total present worth costs. It develops a multi-objective formulation for the scheduling expansion problem which enables cost and equity to be traded-off.

Introduction

Typically the demand for urban water resources increases with population growth. Capacity expansion involves the provision of additional yield by increasing the storage of existing infrastructure and the construction of new infrastructure tapping new sources of water or increasing storage. In its simplest manifestation capacity expansion deals with sizing reservoirs - for example, Khaliquzzaman and Subhash [1] developed a model for sizing multiple reservoirs, while Mousavi and Ramamurthy [2] proposed an optimization method to determine the optimal multi-reservoir system design for water supply. Other studies have explored capacity expansion options beyond sizing reservoirs – they include developing a water supply system layout [3], designing a water distribution system [4] and developing a drought management plan [5].

All the aforementioned studies have focused on decisions at the start of 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 dynamics of growth may nonetheless favor smaller projects staged over the planning period. To analyze this trade-off several studies have considered expansion scheduling [6-14]. In these studies, the objective was to schedule a set of capacity expansion projects that minimized the total present worth cost.

The high capital costs and environmental impacts associated with expanding or building major urban water infrastructure warrant investigation of dynamically scheduling system operating rules such as reservoir operating rules, demand reduction polices and drought contingency plans, as a way of delaying or avoiding the expansion of water supply infrastructure [9, 15]. Lund [9] incorporated conservation rules into the scheduling capacity expansion problem. He demonstrated the benefit of using conservation rules to defer water treatment plant expansion. In Lund's study the present worth of conservation cost and capacity expansion cost was minimized to find the optimum time of adding 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. This raises a socially-sensitive equity issue.

In this paper we propose application of multi-objective optimization for scheduling capacity expansion in an urban system with consideration of equity over the planning period. The paper is organized as follows: First, a description of the scheduling expansion concept is presented. Then the formulation of the multi-objective optimization problem for scheduling expansion is presented. Finally a case study involving the Canberra water supply system is presented to compare the results of single- and a multi-objective capacity expansion.

Formulation of Multi-Objective Scheduling Capacity Expansion Problem

Scheduling expansion problems have typically been formulated to find the timing of predefined projects that minimizes the total present worth cost (PWC). Indeed, given this perspective, the main aim is to find the best sequence of projects [16]. However, projects often can be established at different scales. Thus, the scheduling capacity expansion can be generalized to find the optimum timing and scale of predefined projects.

Figure 1 illustrates the scheduling process. Given the initial yield of the system is d_0, the system can meet demand up to time T_1. At time T_1, a decision is made to add extra yield E_1. As a result, system yield will exceed demand until time T_2. Similarly 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 change points is called a planning stage.

Let x_i denote a vector of decision variables at change point i occurring at time T_i. The vector x_i defines the project or set of decisions for the i^{th} planning stage and can represent a mix of infrastructure options and operating rules.

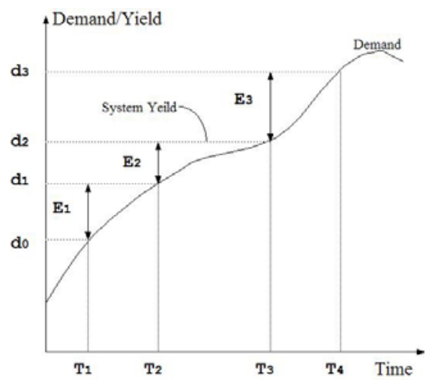

Figure 1. Schematic of scheduling expansion over a planning period.

For the urban problem, the present worth cost of a particular sequence of projects over M planning stages $X = \{x_1,..x_M\}$ can be expressed as

$$\sum_{t=0}^{T} \frac{C_t(x_{1:t}) + O_t(x_{1:t}) + CR_t(x_{1:t}) + U_t(x_{1:t})}{(1+r)^t} \tag{1}$$

where T is number of years in planning period, r is the discount rate, $x_{1:t} = \{x_1,..x_m : T_m \leq \text{t} < T_{m+1}\}$ is the sequence of projects or decision vectors made on or before year t, C_t is the cost of infrastructure investments in year t, O_t is the operational cost for year t, CR_t is the cost associated with restricting demand according to the drought management plan and U_t is the cost of unplanned demand shortfalls in year t.

Eq. (1) is traditionally applied to capacity expansion problems in conjunction with demand restriction rules. However, discounting restriction costs results in the same frequency and severity of restrictions in the future being costed less than the same level in the present. As a result, minimization of Eq. (1) can lead to a higher frequency and severity of restrictions in the future, a situation which often would be politically unacceptable on social equity grounds. To overcome this practically important shortcoming, the restriction cost can be treated separately from infrastructure and operational costs by employing multi-objective optimization. This allows exploration of the trade-off between operational and infrastructure costs and equity of the restriction costs. The first objective minimizes the present worth of infrastructure and operating costs over the planning period. The second objective minimizes the average of cost of actual restrictions averaged over the M planning stages – no discounting is employed so that the burden of restrictions on the community is treated equally regardless of the planning stage. The third objective minimizes the standard deviation of actual cost of restrictions over the planning stages to maximize equity over the planning stages.

Restriction frequencies, and as a consequence, restriction costs, are dependent on future climate scenarios. To capture the uncertainty in future climate scenarios it is necessary to run the simulation model of the urban water resource system with many replicates of the future climate. Thus the three objectives can be formulated as

$$\underset{X}{Min}\ \frac{1}{L}\sum_{l=1}^{L}\sum_{t=0}^{T} \frac{C_{tl}(x_{1:t}) + O_{tl}(x_{1:t}) + CR_{tl}(x_{1:t}) + U_{tl}(x_{1:t})}{(1+r)^t} \tag{2}$$

$$\underset{X}{Min} \frac{1}{M}\sum_{m}^{M} \frac{1}{L}\sum_{l=1}^{L} CR_{ml} \tag{3}$$

$$\underset{X}{Min} \sqrt{\frac{1}{M}\sum_{m}^{M}\left(\frac{1}{L}\sum_{l=1}^{L} CR_{ml} - \frac{1}{M}\sum_{m}^{M}\frac{1}{L}\sum_{l=1}^{L} CR_{ml}\right)^2} \tag{4}$$

where L is the number of climate replicates and CR_{ml} is actual total restriction cost over planning stage m for the l^{th} future climate replicate.

The cost of restrictions can be expressed as [18]

$$CR_r = \frac{\varepsilon}{1+\varepsilon} p_1 q_1 [1-(1-R)^{\frac{1+\varepsilon}{\varepsilon}}] \tag{5}$$

where R is the fractional reduction in water consumption of a particular household in response to water restrictions, p_1 (\$/KL) is the current price, q_1 (KL/month) is the household outdoor consumption and ε is the price elasticity.

Urban Water Resource Case Study

The case study seeks to identify the optimal capacity expansion scheduling for the headworks water supply system serving Australia's capital city, Canberra. A network linear programming simulation model was developed using WATHNET [18]. In the WATHNET schematic, shown in Figure 2, the Canberra urban area is represented by a single demand node serviced by large reservoirs in two major catchments, Corin and Googong. In this study, the population of Canberra has been increased to 175% of the current population to enable investigation of a system in a highly stressed state. Releases from the reservoirs have to meet, not only the consumptive needs of the Canberra urban area, but also environmental flow requirements defined in water authority's operating license.

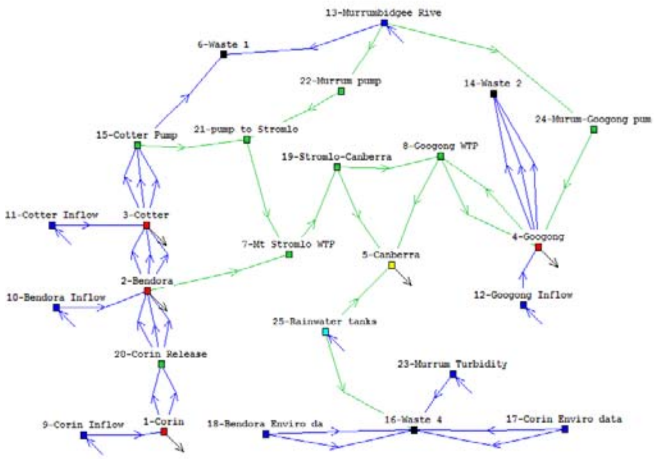

Figure 2. WATHNET schematic of Canberra water supply system.

A planning period of 30 years was used with three planning stages of length 10 years. The first set of decisions x_1 is implemented at the start of year 1, the second set x_2 at the start of year 11, and so on. In all 30-year simulations, reservoirs are assumed to be full at the start of the first stage. The demand growth rate and discount rate were set to 1.2% and

5% respectively. To allow for the stochastic nature of inflows into reservoirs, all scenarios were run for 50 replicates. Each replicate has different inflow series for all reservoirs.

Six decisions describing a mix of operational and infrastructure options can be optimized at each planning stage. These decisions and their lower and upper limits are presented in Table 1. When an infrastructure decision is equal to zero, it means that infrastructure option is not implemented. Once the first two infrastructure options are implemented, they cannot be augmented at a future planning stage. In contrast, the third infrastructure option involving rainwater tanks can be augmented in future stages.

Table 1. List of decision variables.

Decision description	Lower limit	Upper limit	Category
Cotter capacity(ML)	0	100000	Infrastructure
First restriction trigger	0	1	Operational
Trigger intervals	0.05	0.25	Operational
Murrumbidgee diversion (ML)	0	6000	Infrastructure
Murrumbidgee pump trigger	0	1	Operational
Number of houses with tanks	0	15000	Infrastructure

To investigate the importance of scheduling capacity expansion projects over a planning period, four scenarios, summarized in Table 2, are considered. They differ in timing of their infrastructure and operational decisions. In Scenario 1, all the decisions are made at start of the first planning stage. In Scenario 2, all infrastructure decisions are made at the start of the first planning stage, while operational decisions are flexible in the sense they can be changed in the first, second and third planning stages. In Scenario 3, all the decisions can be made at any planning stages subject to 0-1 constraints on the infrastructure options. The first three scenarios minimize a single objective, namely PWC. The fourth scenario minimizes three objectives with the same decision timing as Scenario 3.

Table 2. Case study scenarios.

Scenario	Objectives	Timing of decision	
		Infrastructure	Operational
Sc 1	Minimize PWC	Stage 1	Stage 1
Sc 2	Minimize PWC	Stage 1	Any stage
Sc 3	Minimize PWC	Any stage	Any stage
Sc 4	Eq. (2) to (4)	Any stage	Any stage

In this study eMOEA is employed as the optimization method because of its good performance when compared with other available evolutionary methods [19]. Since eMOEA is a probabilistic method, it is necessary to run the optimization with different initial seed numbers. In this study all scenarios were run 10 times. The results report the best out of 10 runs. The probability of crossover was set to one, while the probabilities of mutation and inversion were set to 0.01 and 0.005 respectively.

Results

Table 3 presents the results for the first three scenarios. To better understand the differences between the scenarios, the total PWC is disaggregated into its component values. Although the capital and operational cost is almost the same for all scenarios, the discounted restriction costs vary significantly.

Table 3. Results for first three scenarios.

Scenario	Total PWC ($ m)	Capital and Operational cost ($ m)	Discounted restrictions cost ($ m)	Actual restriction cost for first stage ($ m)	Actual restriction cost for second stage ($ m)	Actual restriction cost for third stage ($ m)	Average of actual restriction cost over three stages ($ m)	Standard deviation of actual restriction costs over three stages ($ m)
Sc1	462	393	69	60178	50.6	99.7	57.3	54.1
Sc2	445	391	54	0	59.4	89.6	49.6	50.5
Sc3	444	396	48	56099	34.4	53.2	35.9	36.9

Scenario 1 has the maximum discounted restriction cost because, in this case, the optimizer had to select all the decisions at the beginning of the first planning stage. The discounted restriction cost of Scenario 2 is smaller because allowing flexible operational rules over planning stages reduces the chance of imposing unnecessary restrictions. The optimal strategy is to provide flexibility in timing and sizing of both infrastructure and operational decisions. This is clearly demonstrated in Table 3 where Scenario 3 has the lowest total PWC. However, it is noted that virtually all of the benefit of scheduling comes from allowing the operational decisions to change over time.

In all the scenarios in Table 3, the third planning stage has a larger restriction cost compared to the second one and similarly the second stage has a larger restriction cost compared to the first stage. There are two factors responsible for this. First, the use of discounted restriction costs encourages the optimizer to postpone restrictions to future stages because that is the optimal strategy. Second, the system was initially full, so the chance of restrictions in the first planning stage is reduced - the flexible timing of operational decisions in Scenarios 2 and 3 exploits this initial condition.

Scenario 4 attempts to treat all planning stages equitably with respect to the burden of restrictions. Figure 3 presents the Pareto frontier for this scenario. There is a trade-off between the infrastructure/operational costs and the cost of imposing restrictions. Indeed, the restriction cost can be very large in the absence of significant infrastructure investment. The figure also shows that restriction costs are virtually eliminated when the infrastructure/operational cost exceeds $800 million – it is noted this is far in excess of the $444 million total PWC obtained in Scenario 3.

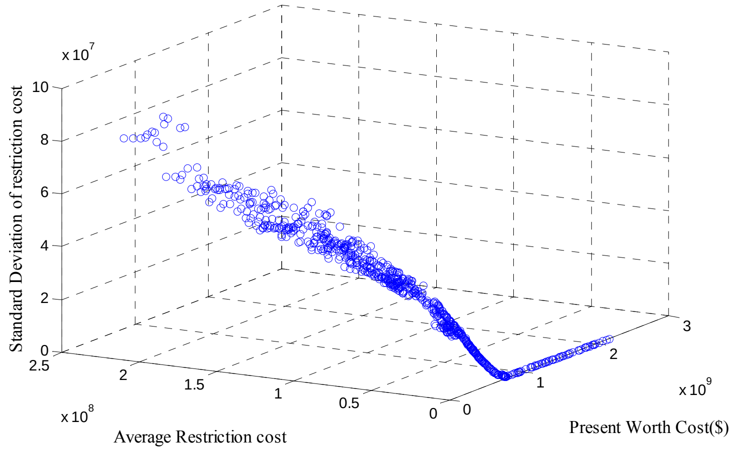

Figure 3. Pareto frontier for scenario 4.

Conclusion

Urban population growth will result in a greater future demand for water. To cater for this growing demand, a variety of options are available including operational decisions such as imposing restrictions and promoting more efficient water use and infrastructure investments such as building dams. Because the water resource system is facing a growing demand, its performance will change over time. As a result, the main challenge is to find the best combination of these options both in scale and 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. This study has demonstrated the importance of scheduling operational as well as infrastructure decisions over the planning period. Indeed in the Canberra case study, virtually all of the benefit of scheduling over time was attributed to operational decisions.

Some studies have considered the use of conservation and restrictions to delay infrastructure investment. However, it was shown that the minimum total present worth cost strategy can lead to more severe restrictions in future planning stages resulting in socially-unacceptable inequity. To remedy this problem, the scheduling problem can be reformulated as a multi-objective optimization allowing the trade-off between cost and equity to be explored. The Canberra case study demonstrated that the multi-objective approach produced far more equitable solutions than minimization of total present worth cost.

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