Optimal conjunctive-use operations and plans

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Abstract. Heuristic or intuitive rules based on experience may not be efficient when applied to the management of water supply systems that contain both surface and subsurface storage. In particular, rules that assign subsurface storage the role of a backup to surface storage do not recognize the different capabilities of surface and subsurface storage. We demonstrate how to incorporate the different capabilities of surface and subsurface storage in appropriately cautious long-term control of conjunctive-use systems. We also demonstrate how these results may be used to evaluate the benefit of adding groundwater supplies to an existing surface water supply system.

1. Introduction

Conjunctive use of groundwater and surface water can enhance the reliability of water supplies by providing independent sources that have distinctly different costs and constraints [*Fisher et al*., 1995; *Lettenmaier and Burges*, 1979]. Groundwater's role in stabilizing supplies (through improving reliability and reducing the impact of drought) can be of even greater value than its role in adding to total quantity [*Tsur*, 1990; *Tsur and Graham-Tomasi*, 1991]. Unfortunately, the potential for using the subsurface as a natural storage facility has not been fully developed, and most large water supply systems continue to depend exclusively on surface water supplies [*van der Leeden et al*., 1990]. One barrier to the development of conjunctive-use systems is the lack of guidelines on how to operate such systems and how to evaluate the benefit of capacity expansion. As a result, groundwater has traditionally been used only as a backup supply for times of shortage [*Lettenmaier and Burges*, 1979].

Surface and subsurface storage have different operating costs and constraints. Surface storage can be filled and drained rapidly, while groundwater pumping and recharge rates are limited and may entail additional operating costs. However, aquifer storage capacity considerably exceeds the available surface storage in many watersheds [*Buras*, 1963; *California Department of Water Resources*, 1994]. Beyond these differences, surface and subsurface storage differ in their environmental consequences, water quality, flood control ability, power generation potential, losses from seepage and evaporation, and legal control [*van der Leeden et al*., 1990].

Such differences suggest that the control of surface and subsurface storage should be quite different. *Lettenmaier and Burges* [1979, p. 1] observe that "in contrast to the rather long-term failure modes encountered in excessive reliance on groundwater supplies, shorter scale (e.g., annual or seasonal) failures may result from exclusive use of surface supplies. The difference in time scales results because typical surface storage reservoir volumes are much smaller compared to abstractions than are groundwater supplies." By taking advantage of the distinctly different characteristics of surface and subsurface storage, efficient operation policies can produce significant improvements in supply reliability. Also, surface and subsurface storage yield significantly different water supply benefits when added to an existing system. These benefits depend on the current mix of surface and subsurface storage [*Lettenmaier and Burges*, 1979] and the uncertainty of water supplies [*Tsur*, 1990].

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Efficient real-time control policies can be identified using simulation and optimization, or "systems analysis." By using a mathematical model that simulates the structure and dynamics of a conjunctive-use system we can conveniently simulate and evaluate proposed management options. Also, by applying optimization methods we can quickly and efficiently identify the best options for control and planning when a range of options exists.

Systems analysis allows managers to identify control policies for new or modified systems for which there is insufficient operating experience to rely on heuristic control methods [*Oliveira and Loucks*, 1997]. In particular, for conjunctive use, systems analysis can identify control policies that efficiently ration water supplies and allocate stored water between surface and subsurface storage. In addition, systems analysis can be used to explicitly evaluate the benefit of adding surface and/or subsurface storage to an existing water supply system. Using these methods, managers can objectively balance the reliability and operating costs of various options with the capital costs of these options [*Cummings and Winkelman*, 1970].

This paper will identify efficient real-time control policies and the benefit of capacity expansion in a simple conjunctive-use system with an uncertain supply. This is accomplished using two innovations. The first innovation is the application of new gradient dynamic programming methods [*Foufoula Georgiou and Kitanidis*, 1988; *Philbrick*, 1996] to mitigate the "curse of dimensionality" that prevents the application of dynamic programming to stochastic problems with numerous state variables [*Johnson et al*., 1993; *Provencher and Burt*, 1994; *Yakowitz*, 1982]. The second innovation is the application of a model that incorporates capacity constraints as state variables, allowing the evaluation of a wide range of expansion alternatives while simultaneously identifying the best operating policies.

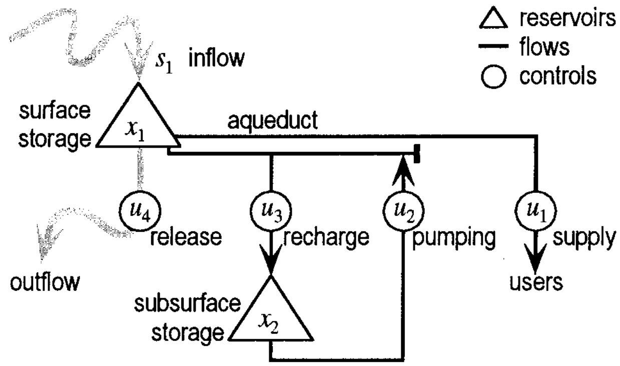

Figure 1. The conjunctive-use model.

2. Background and Solution Method

When inputs are uncertain, appropriate control decisions cannot be identified by a predetermined control schedule because information about future inputs, such as streamflow, is not available. Instead, managers make "real-time" decisions that use the information available only when the decisions are made and not earlier. Thus the problem is how to optimize control policies rather than control schedules.

The goal is to identify control policies that achieve the best system performance from current and future operations. When it is necessary and appropriate to quantify the measure of performance, it may be expressed in monetary terms as a "cost." The goal of systems analysis is, therefore, to minimize the expected cost of operations accumulated over a multiperiod time horizon. If the cost of operating decisions (identified by a vector $\mathbf{u}$) for each period is defined by a function $C_{t_i}(\mathbf{u})$, then the accumulated cost of operations is

$$V = \sum_{i=1}^{N} (1 - r)^i C_{t_i}(\mathbf{u}) \tag{1}$$

for an N-period horizon using a discount rate r. To identify efficient decisions, it is necessary to consider the current conditions of a system that influence operations. These conditions identify the "state" of a system and are identified by a vector of variables, $\mathbf{x}$.

Feasible decisions are those that satisfy the physical and policy constraints imposed on operations. For example, the releases from a reservoir are constrained by the capacity of outlet works, by the amount of water in storage, and perhaps by the flow maintenance requirements downstream. The capacity of outlet works and flow maintenance requirements result in simple bounds on release decisions. In contrast, the amount of water in storage changes with time and depends on prior release decisions and uncertain inflows. The resulting constraint on release decisions is complex and varies with time, and the amount of stored water is a condition that influences operations and identifies part of a system's state.

Such changing conditions can be defined by state variables whose evolution is modeled by transition equations

$$\mathbf{x}_{(t_{i+1})} = \mathbf{T}_{t_i}(\mathbf{x}_{(t_i)}, \mathbf{u}_{(t_i)}, \mathbf{s}_{(t_i)}) \tag{2}$$

Evolution during interval $[t_i, t_{i+1}]$ depends on the initial state $\mathbf{x}_{(t_i)}$, decisions $\mathbf{u}_{(t_i)}$, and uncertain inputs $\mathbf{s}_{(t_i)}$ (if present). If bounds restrict the evolution of the state variables (e.g., the maximum and minimum capacity of a reservoir), these bounds will also constrain feasible decisions, depending on the values for $\mathbf{x}_{(t_i)}$ and $\mathbf{s}_{(t_i)}$.

When all inputs to a system are certain (i.e., fully knowable in advance), the decisions in each stage that are "best" (lowest cost) are those that minimize the accumulated cost by solving

$$F_{t_1}(\mathbf{x}) = \min_{\mathbf{u}_{(t_1)}, \ldots, \mathbf{u}_{(t_N)}} \{V\} \tag{3}$$

subject to the various physical and policy constraints. Given an initial state $\mathbf{x}_{(t_1)}$ and a schedule of control decisions $[\mathbf{u}_{(t_1)}, \cdots, \mathbf{u}_{(t_N)}]$, the future states $[\mathbf{x}_{(t_2)}, \cdots, \mathbf{x}_{(t_{N+1})}]$ of a system are completely defined. As a result, control of the system can be specified by a single best control schedule.

If there are uncertain inputs, appropriate control decisions cannot be identified by a predetermined control schedule because the future states of a system are not known in advance. Instead, decisions must be given by a series of control policies $\{\mathbf{U}_{(t_1)}, \cdots, \mathbf{U}_{(t_N)}\}$ that specify control decisions for a range of possible states. The best control policies are those that minimize the expected accumulated cost by solving

$$F_{t_1}(\mathbf{x}) = \min_{\mathbf{U}_{(t_1)}, \ldots, \mathbf{U}_{(t_N)}} \{\mathrm{E}_{\mathbf{s}_{(t_1)}, \ldots, \mathbf{s}_{(t_N)}} \{V\}\} \tag{4}$$

subject to the various physical and policy constraints.

Using the "principle of optimality" for dynamic programming [*Bellman*, 1957], the difficult stochastic problem posed by (4) can be decomposed into a series of easier-to-solve subproblems:

$$F_{t_i}(\mathbf{x}) = \min_{\mathbf{U}_{(t_i)}} \{\mathrm{E}_{\mathbf{s}_{(t_i)}} \{C_{t_i}(\mathbf{u}) + F_{t_{i+1}}(\mathbf{x})\}\} \tag{5}$$

Instead of considering the practically infinite number of scenarios of a multistage problem, expected cost is calculated, one stage at a time, as a weighted sum of a limited number of scenarios.

Traditionally, this approach has been limited to problems with few periods and no more than two or three state variables. With recent advances it is possible to solve problems with as many as six or seven state variables. In this paper, a second-order gradient dynamic programming method [*Philbrick*, 1996, chapter 5] is applied to a conjunctive-use model with 100 periods and five state variables. In each period and for each initial state the expected cost of the proposed control decisions is calculated as the probability-weighted sum of outcomes using Gaussian quadrature [*Philbrick*, 1996, chapter 7; *Press et al.*, 1992].

3. Problem Description

We consider a hypothetical system model similar to that discussed by *Buras* [1963, 1972] and summarized by *Yakowitz* [1982] while also using characteristics of the East Bay Municipal Utilities District (EBMUD) system of Oakland, California [*East Bay Municipal Utility District*, 1992; *Fisher et al.*, 1995]. Increasing demands for water in the district and for more senior appropriators have prompted EBMUD to consider several options to prevent deterioration of its water supply reliability. These options include building a new surface reservoir or adding groundwater storage to their existing surface storage system.

3.1. System Model

The hypothetical system contains surface storage and aquifer storage components as illustrated in Figure 1. The system is described by the following: (1) control variables, $\mathbf{u}$, that include decisions to supply water to meet demand and to allocate

Table 1. Variables of the Conjunctive-Use Model

Variable	Type	Definition	Minimum*	Maximum*
u_1	control	supply to users, per year	0	600
u_2	control	groundwater pumping, per year	0	100
u_3	control	groundwater recharge, per year	0	50
u_4	control	release downstream, per year	0	infinite
x_1	state	surface reservoir storage	0	200
x_2	state	subsurface reservoir storage	0	500
s_1	stochastic	inflow from streams	0	infinite

*Values are given in thousands of acre-feet (1 ac ft is 1234 m^3).

water between surface and subsurface storage, (2) state variables, **x**, that define the amount of water currently stored separately in surface and subsurface reservoirs, and (3) stochastic variables, **s**, that define reservoir inflows (Table 1).

The state of the system evolves under the influence of control decisions and reservoir inflows according to the linear transition equations

$$(x_1)_{t+1} = (x_1 - u_1 + u_2 - u_3 - u_4 + s_1)_t \tag{6a}$$

$$(x_2)_{t+1} = (x_2 - u_2 + u_3)_t \tag{6b}$$

Equations (6a) and (6b) describe the change in surface and subsurface storage levels during each period of operation, or "stage." The ending surface storage is the sum of the beginning storage $x_{1,(t)}$, inflow $s_{1,(t)}$, and groundwater pumping $u_{2,(t)}$ minus the water supplied to users $u_{1,(t)}$, groundwater recharge $u_{3,(t)}$, and release downstream $u_{4,(t)}$. The ending subsurface storage is the sum of the beginning storage $x_{2,(t)}$ and recharge minus pumping. In addition, the state of the system evolves subject to bounds that constrain feasible decisions and attainable states (Table 1).

3.2. Demand, Streamflow, and Storage

The model uses yearlong stages; therefore supply and allocation decisions are updated annually. Though practical application of real-time control to a system requires more frequent updates, yearlong stages produce a model that does not contain the added complexity of seasonality. Yearlong stages also reduce the significance of streamflow autocorrelation and correlation with other indicators such as snowpack measurements. This produces results that are easier to interpret and that more clearly illustrate the impact that differences in surface and subsurface storage have on optimal control and on the benefit of capacity expansion [*Oliveira and Loucks*, 1997].

Water demand is a constant 600 thousand ac ft (TAF)/yr (1 ac ft is 1234 m^3). Streamflows are lognormally distributed, with an annual mean of 700 TAF and a standard deviation of 350 TAF. The reservoir capacities that are available to regulate these flows are 200 TAF of surface storage and 500 TAF of subsurface storage. These values are loosely based on the Mokelumne River basin, the future water demand for EBMUD, other appropriators, and streamflow maintenance requirements [*East Bay Municipal Utility District*, 1992].

Reservoirs store water when it is abundant and release water to meet demand when it is scarce. In other words, reservoirs redistribute water in time to improve the reliability of a supply. The greater the variability and uncertainty of a supply, the greater the total storage capacity required. The model incorporates only the uncertainty of annual streamflow and not the additional uncertainty and variability of seasonal streamflow. As a result, the anticipated reliability for the annual model is greater than the reliability for a more realistic seasonal model, given the same storage capacities. In other words, the anticipated reliability for the annual model should be comparable to the reliability of a real system with greater storage capacity.

3.3. Value Model

In each stage the cost of control decisions **u** is the sum

$$C(\mathbf{u}) = \text{shortage cost} + \text{pumping cost} + \text{recharge cost} \tag{7}$$

Shortage cost is the loss from rationing that leaves some demand for water unsatisfied and is a function of the water supply decision u_1. Pumping and recharge are operating costs that result from allocating stored water between surface and subsurface storage by a decision to pump u_2 or recharge u_3. This study uses a realistic estimate of shortage cost with conservative (i.e., high) estimates of pumping and recharge costs to ensure that the model captures the disincentive that these costs have on the use of subsurface storage. As a result, the model tests the value of aggressive groundwater management even when pumping and recharge costs are significant.

3.3.1. Shortage cost. The impact of urban water shortage is severe and grows rapidly with the degree of rationing. As a result, system managers have an incentive to incur modest rationing and operating costs when these reduce the likelihood of more severe future rationing. In other words, efficient real-time control policies include management decisions that "hedge," sacrificing some current water use benefits to ensure future benefits.

Quantifying the benefits and costs of water use can be difficult and subject to dispute [*Hashimoto et al.*, 1982; *Rogers and Fiering*, 1986]. As a result, few reservoir management studies attempt to estimate actual shortage costs despite the important impact that these costs have on hedging. For example, *Fisher et al.* [1995] compare the impact of various capacity-expansion alternatives for the EBMUD system by evaluating only the capital and operating costs of the various alternatives. Surrogate indices [*Fiering*, 1982; *Hashimoto et al.*, 1982; *Hsu*, 1995] and other methods [*Fontane et al.*, 1997; *Owen et al.*, 1997] have been developed, though these still require implicit or explicit estimates of water use impacts.

In contrast, the current model uses an explicit estimate of the cost of rationing [*Philbrick*, 1996, chapter 10]. This cost can be interpreted as the consumers' willingness to pay [*Dandy*, 1992; *Lund*, 1995] for domestic water use and is estimated over the range of possible water supply conditions by assuming that the elasticity of demand (i.e., the sensitivity of demand to changes in price) for water is constant [*Martin and Thomas*, 1986]. Elasticity is defined as the constant of proportionality α given by

$$\alpha = \lim_{\Delta P \to 0} \left\{ \frac{\Delta Q/Q}{\Delta P/P} \right\} = \frac{dQ/Q}{dP/P} \tag{8}$$

where Q is the quantity of water available and P is the price consumers are willing to pay to obtain an additional unit of water [*Hanke*, 1980]. The constant α is negative because an increase in price usually results in a decrease in demand. Demand is "inelastic" with $-1 < \alpha < 0$ because large changes in price are associated with small changes in supply. The elasticity of demand decreases (has a smaller negative value) if less time is available to adjust water use to changing water supply conditions.

A cost function can be identified given an appropriate value for elasticity and a single set of values for price and demand [*Dandy*, 1992]. An elasticity of $\alpha = -0.33$ is assumed for the annual supply decisions of the current model. This value seems reasonable given the elasticities estimated by other authors [*Billings and Agthe*, 1980; *Danielson*, 1979; *Martin and Thomas*, 1986; *Mercer and Morgan*, 1989; *Moncur*, 1987, 1989]. A nominal price of \$200/ac ft is also assumed on the basis of recent California water prices [*California Urban Water Agencies*, 1991; *East Bay Municipal Utility District*, 1992; *Fisher et al*., 1995; *Howitt*, 1994; *Jercich*, 1997; *McClurg*, 1992a, b]. Using a nominal annual supply of $u_1^{\max} = 600$ TAF, the shortage cost for an annual supply of u_1 is

$$\text{shortage cost} = \$60{,}000{,}000[(u_1/u_1^{\max})^{-2} - 1] \tag{9}$$

Shortage cost is the sum of the incremental costs for each unit of rationing below $u_1^{\max}$. When there is no rationing, $u_1/u_1^{\max} = 1$. When rationing is unavoidable or is used to hedge against future shortages, $u_1/u_1^{\max} < 1$.

At low levels of rationing, the marginal cost of shortage (i.e., the additional cost for losing the next acre-foot) is \$200/ac ft. As rationing increases, the marginal cost of each acre-foot of shortage increases, consistent with constant elasticity. At extreme levels of rationing, the marginal cost escalates rapidly: \$200,000/ac ft (\$0.16/L) at 90% rationing (though average cost is only \$1100/ac ft). Consistent with an inability to survive without some water, the price becomes infinite as supplies approach zero. As a result, the assumption of constant elasticity produces a cost function that realistically captures the impact of significant water shortages on domestic consumption. Such a cost function will encourage cautious decisions that avoid severe rationing during droughts while allowing appropriate use when water is abundant. In contrast, previous studies have often used quadratic cost functions [*Bogle and O'Sullivan*, 1979; *Burt*, 1967; *Foster and Beattie*, 1979; *Hsu*, 1995; *Johnson et al*., 1993; *Kitanidis and Andricevic*, 1989; *Zarnikau*, 1994]. A quadratic cost function may be appropriate when a temporary loss of water produces a limited welfare loss (perhaps when water is used as a resource for agriculture or industry). However, a quadratic cost function is not appropriate when a loss of water produces welfare losses that increase more dramatically (such as when water is for domestic use).

3.3.2. Pumping cost. For pumping lifts of 100 ft (~30.5 m) the cost of electricity is about \$10/ac ft. These costs increase when pumping rates increase, based on specific well capacities. For example, specific well capacities in the Central Valley of California are typically of 35–60 gpm/ft (~0.01 m^3 s^{-1} m^{-1}) [*California Department of Water Resources*, 1967]. Additional costs can be expected for the operation and maintenance for a well field of perhaps 50–100 large-capacity wells.

For the current model, the marginal cost of pumping starts at \$40/ac ft and increases linearly to \$80/ac ft when pumping at the maximum annual rate of $u_2^{\max} = 100$ TAF. This cost should be sufficiently high (under most conditions) to capture the impact that significant pumping lifts have on discouraging the use of subsurface storage. The resulting shortage cost in a yearlong stage is

$$\text{pumping cost} = \$4{,}000{,}000(u_2/u_2^{\max})[1 + 0.5(u_2/u_2^{\max})] \tag{10}$$

Equation (10) specifies only the variable cost of system operation and does not include the capital costs for the installation and development of a well field. For example, *Fisher et al*. [1995] estimate the costs of drilling and pump installation to be about \$25,000 per well.

The current model does not consider the impact that recharging and pumping decisions have on future pumping lifts since this impact is highly variable, depending on the well distribution and on the aquifer characteristics. A straightforward method of capturing this impact is to model both specific well capacity (dependent on u_2) and regional drawdown (dependent on aquifer storage x_2). Additional state variables may be included to represent the distributed characteristics of a well field or the persistence of local water level changes from earlier pumping or recharge. However, studies that incorporate complex models [*Andricevic and Kitanidis*, 1990; *Basagaoglu and Yazicigil*, 1995; *Burt*, 1976; *Georgakakos and Vlatsa*, 1991; *Lee and Kitanidis*, 1991; *Provencher and Burt*, 1994; *Reichard*, 1995] have only been solved by optimization methods that are approximate.

3.3.3. Recharge cost. Recharge cost is highly variable, depending on the methods used and the character of the sites available for implementing a recharge program. Methods may include surface spreading, injection, and enhanced natural recharge (e.g., by structural and institutional arrangements that replace groundwater pumping with surface supplies during wet years). The amount of land and maintenance required for recharge is highly variable, depending on soil type, infiltration rate, and subsurface geology. Also, the cost of establishing and maintaining structural and institutional arrangements can be significant because of government regulations and the diversity of interests that must be considered.

For the current model, the marginal cost of recharge is a constant \$40/ac ft. This could represent the cost of water treatment (prior to recharge), maintenance of facilities (e.g., resurfacing spreading ponds to reduce clogging), pumping (to deliver water to appropriate recharge sites), or water purchase (when in surplus). This cost is sufficiently high to capture the impact that significant recharge efforts may have on discouraging the use of subsurface storage. The resulting recharge cost in a yearlong stage is

$$\text{recharge cost} = \$2{,}000{,}000(u_3/u_3^{\max}) \tag{11}$$

As with (10), (11) specifies only the variable cost of system operation and does not include the capital cost for the land or facilities required to recharge groundwater.

4. Control Policy Results

In the operation of water supply systems, control policies should consider the impact that current decisions have on future costs. This is important because current control decisions limit future management options. As a result, managers have an incentive to sacrifice some current performance (i.e., by incurring short-term costs) to improve future performance. By trading some short-term benefits for long-term benefits, managers hedge.

Hedging is especially important when variable and uncertain system inputs can produce very damaging outcomes. For example, the uncertainty of water supplies can produce shortages whose costs are extreme. In these situations the marginal cost (per unit of deviation) from some target is usually a nonlinear function of the deviation. The dramatic and nonlinear increase in shortage costs gives managers an incentive to moderately ration supplies if this can reduce the future costs of potentially severe rationing.

To identify control policies for the conjunctive-use model that identify an appropriate level of hedging, we minimized the expected cost of water rationing, pumping, and recharge using gradient dynamic programming. In addition, the expected accumulated cost (from water rationing, pumping, and recharge) that results from the application of these policies is identified for any initial state.

Control decisions were identified assuming foresight of the current year's inflow, as this more closely represents real operations [*Tsur*, 1990]. Interannual uncertainty is captured by calculating cost as an expected value evaluated over the current inflow distribution using Gaussian quadrature. In practice, shorter periods are used, and control decisions are based on a sophisticated prediction of streamflow, which is updated frequently over the course of a year.

Using foresight of current inflow, the actual division of water between initial surface storage and current inflow does not influence the control decisions or the accumulated cost. To simplify the illustration of the solution, we define "available surface water" as the current volume given by the sum $(x_1 + s_1)$. Available surface water has no maximum bound, so we illustrate results only for the available surface water <1000 TAF. We also define "available groundwater" simply as the current volume of subsurface storage x_2.

Results are presented for the first stage of a 100-year time horizon using a 4% annual discount rate $(r = 0.04)$. Control policies and the accumulated cost converge to steady state values after a few decades, so the results identify the infinite-horizon, steady state solution. This convergence is promoted by the discount rate; however, we observed that the discount rate has only a small impact on control policies and the annual benefits of capacity expansion. Though a discount rate reduces the value of hedging, the future cost of supply and allocation decisions remains significant.

4.1. Supply Policy

Figure 2 displays the supply policy as a function of surface water and groundwater levels. Because pumping is limited to 100 TAF/yr, rationing is required when surface water supply is low even if a sufficient groundwater supply is available. The release to users must be less than the sum of available surface water and pumping. In Figure 2 this is indicated by vertical portions of the contours. When available groundwater is below 100 TAF, there is insufficient groundwater for maximum pumping. As surface water and groundwater levels increase, the supply increases until plateauing at the maximum of 600 TAF/yr.

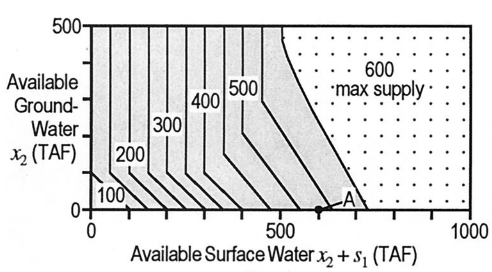

Figure 2. Supply policy: release (thousand ac ft (TAF)/yr) to users as a function of water available in the current year.

Figure 2 shows that rationing (i.e., hedging) is appropriate even when sufficient surface water is available to meet demand. For example, at point A there is sufficient water to meet all demand for a year. Instead, only 530 TAF is released to users, and the remaining water is stored to hedge against future shortages. Rationing is appropriate when available surface water is limited (400–730 TAF) and groundwater is low. Under these conditions the cost of rationing in the current period is less than the expected cost of potentially severe rationing in the future. The importance of hedging in supply policies has been similarly demonstrated for a single water supply reservoir by the work of *Hashimoto et al.* [1982].

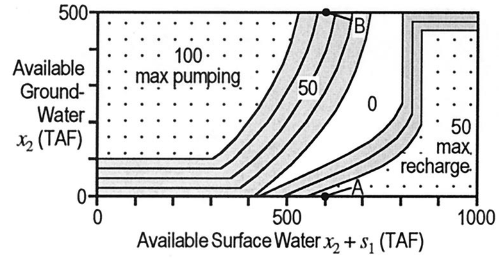

Figure 3. Pumping and recharge policies: transfers (TAF/yr) from and to groundwater as a function of water available in the current year.

4.2. Allocation Between Surface and Subsurface Storage

Figure 3 displays the pumping and recharge policies. In effect, these policies determine how stored water should be allocated between surface and subsurface storage. Common sense tells us that pumping is beneficial when surface water levels are low and groundwater levels are high and that recharge is beneficial under the opposite circumstances. The difficulty is identifying exactly when to start pumping and when to start recharging.

4.2.1. Pumping policy. Figure 3 shows that maximum pumping is appropriate whenever available surface water is low and any groundwater is available. When available groundwater is less than the maximum pumping capacity of 100 TAF/yr, the pumping contours are horizontal.

Figure 3 shows that hedging is needed at all groundwater levels to reallocate available supplies between surface and subsurface storage in spite of operating costs. It might be thought that pumping should be determined solely by the need to meet current demand; however, these results show that pumping should be reduced to save some groundwater, even in the presence of moderate rationing (less than ~200 TAF/yr). Figure 3 also shows that if the groundwater level is high, pumping should be used to replenish surface water supplies. For example, at point B there is 600 TAF available surface water and 500 TAF available groundwater. Though all demands can be met with no pumping, pumping should continue at a moderate rate. Because the pumping rate is constrained, water stored in

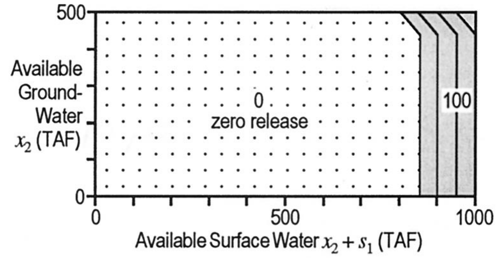

Figure 4. Release policy: release (TAF/yr) downstream as a function of water available in the current year.

the surface reservoir reduces the severity of rationing with extremely low inflows in subsequent years. Thus it is desirable to shift some portion of the stored water from subsurface storage to surface storage where it is more readily available.

4.2.2. Recharge policy. Figure 3 shows that maximum recharge is appropriate whenever the available surface water is high and groundwater is low (so long as subsurface storage capacity is available). This is especially true when the available surface water exceeds 800 TAF (the sum of maximum demand and surface storage); otherwise, excess water above this level would be released "unused" downstream.

Recharging decisions show the impact of hedging so long as surface water levels are not critically low (below ~430 TAF). It might be thought that recharge should be determined solely by the availability of water in excess of demand and surface storage capacity. However, Figure 3 shows that recharging should be used to transfer some water to the subsurface, even in the presence of moderate rationing. For example, at point A there is 600 TAF available surface water and zero groundwater. There is rationing of 70 TAF/yr (Figure 2), yet recharging should occur at its maximum rate. As with the pumping policy, it is desirable to shift some portion of the remaining stored water from surface storage to subsurface storage. Because surface storage is limited, this ensures that the benefit of current efforts to save water (by rationing) is not lost if the reservoir spills in the following year.

4.2.3. Allocation. In the absence of operating costs, pumping and recharge policies should seek allocations that give the best water supply reliability. These allocations are based on the different capabilities and limitations of surface and subsurface storage: Water stored on the surface may be "lost" if the reservoir subsequently spills. Water stored in the subsurface may be rate limited and not fully accessible during severe shortages. For the conjunctive-use model, the best allocation of stored water lies in the gap between the pumping and recharge contours of Figure 3.

In the presence of operating costs for pumping and recharge, policies should seek better allocations only when the benefit of an improved allocation exceeds the cost of achieving that allocation. There is no incentive to pump and recharge simultaneously because of operating costs. Indeed, water supply conditions for pumping and recharge are separated by a gap where the benefit of reallocation does not exceed the cost.

Aggressive pumping or recharge is appropriate when the benefit of reallocating stored water is large, such as when allocations are far from optimal or when water is scarce. As a result, the gap between pumping and recharge decisions is narrow when storage levels are critically low. The marginal value of stored water is high, and the benefit of an improved allocation exceeds the cost under most conditions. As storage levels increase, the gap widens as the benefit of improved allocation decreases. When supplies are sufficiently large, the gap narrows again as the recharge policy captures water that would otherwise be released downstream.

4.3. Downstream Release Policy

Figure 4 displays the downstream release policy. Water is released downstream only when water levels exceed the demand and opportunities for storage. In the current model, rationing cost is greater than recharge cost because demand is a large fraction of average streamflow. Also, the model does not consider other goals that could encourage additional releases (e.g., releases to preserve storage for flood control or for flow maintenance).

4.4. Expected Cost of System Operations

Figure 5 displays the discounted accumulated cost as a function of the available surface water and groundwater levels. As surface water and groundwater levels decrease, the cost increases and becomes infinite as levels approach zero. Zero supply means that there is no water for any use (including basic necessities). In reality, such critically low supplies are unlikely because (1) extremely low inflows are unlikely, (2) storage levels should rarely approach zero with cautious management, and (3) alternate supplies can usually be found when the price is sufficiently high (i.e., when hauling water by trucks, desalination, and other supply methods become cost effective).

As discussed in section 4.2.3, the best allocation of stored water lies in the gap between the pumping and recharge contours of Figure 3. Figure 5 identifies this allocation as the shaded line where the marginal benefit of surface and subsurface storage is equal. A 45° line represents the possible allocations of a stored water, and the lowest-cost allocation is the tangent of this line to an accumulated-cost contour.

Expected costs do not change when available surface water is >850 TAF because water beyond this amount cannot be used or stored. Such a large surface supply fully meets the maximum demand (600 TAF/yr) while filling the surface reservoir (200 TAF) and recharging at the maximum rate (50 TAF/yr).

4.5. Cost-To-Go

Figure 5 plots the expected accumulated cost of rationing and operations as a function of the available surface water and groundwater, assuming foresight of current inflow $s_{(t_1)}$. This cost is the sum of a known cost for current decisions and an expected cost for future decisions. Future decisions are uncertain because they depend on inflows $\{s_{(t_2)}, \cdots, s_{(t_N)}\}$. In contrast, Figure 6 displays the expected accumulated cost as a

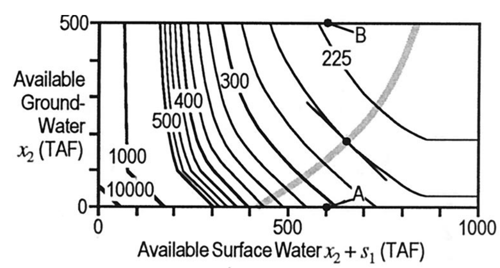

Figure 5. Expected accumulated cost (millions of dollars) as a function of water available in the current year with foresight of the current year's inflows.

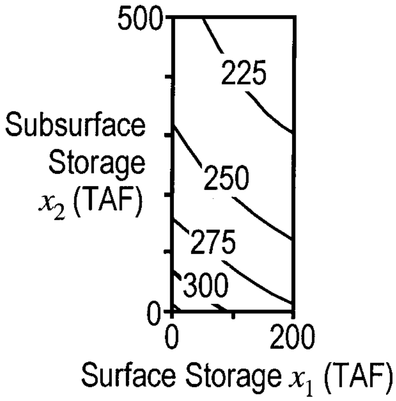

Figure 6. "Cost-To-Go": expected accumulated cost (millions of dollars) from future inflows as a function of the initial storage levels.

function of surface and subsurface storage levels, x_1 and x_2, assuming no foresight. This is the function $F(\mathbf{x})$ that identifies the "cost-to-go" from any state, where both current and future decisions are uncertain and depend on inflows $\{s_{(t_1)}, \cdots, s_{(t_N)}\}$. Because the cost-to-go function expresses future costs strictly as a function of the state, it identifies the relative preference for different states. As a result, this function evaluates the impact that control decisions have on future costs (by their impact on future states of the system).

The costs of Figure 6 are less variable than those of Figure 5 because of the "averaging" over the possible values of current inflow $s_{(t_1)}$. This can be represented by

$$F_{t_1}(x) = \sum_{\mathbf{s}_{(t_1)}} W_{t_1}(\mathbf{s}) f_{t_1}(\mathbf{x}, \mathbf{s}) \tag{12}$$

where $W_{t_1}(\mathbf{s})$ is the probability density function of inflow $\mathbf{s}_{(t_1)}$ and $f_{t_1}(\mathbf{x}, \mathbf{s})$ is the cost function of Figure 5. The average cost of about \$250 million in Figure 6 is consistent with the cost of the "typical" conditions in Figure 5 of around 700 TAF available surface water (because mean streamflow is 700 TAF/yr).

Figure 6 shows that using a discount rate of 4%, the accumulated cost of future operations is roughly \$250 million, and the annual cost is roughly \$10 million (i.e., at 4% the net present value of \$10 million/yr for many years is \$250 million). This cost decreases as levels increase, but the cost is still significant even when reservoirs are initially full. The time horizon is sufficiently long, so that the cost of future shortages is significant. Also, the marginal cost (or benefit) of changing storage levels is not constant; marginal cost is greatest when storage levels are low and also depends on the allocation between surface and subsurface storage. Because these differences are significant (when compared with the current cost of decisions), the control policies hedge.

5. Capacity-Expansion Results

We now extend the conjunctive-use model to evaluate the effect of changing system capacities. This is accomplished by converting the bounds on surface storage, pumping, and recharge from fixed values to variables. To allow these variable capacities, we add three additional state variables, representing pumping capacity x_3, recharge capacity x_4, and additional surface storage capacity x_5. These are assumed to be fixed over the operating horizon, and the three transition equations added to (6a) and (6b) set these state variables equal to their value in the previous stage. Constraints are modified to incorporate these changing capacities as indicated in Table 2.

The advantage of this approach is that the benefits of an infinite number of capacity expansion alternatives can be evaluated while simultaneously identifying the appropriate real-time control policies. As a result, it is possible to identify the best capacity-expansion alternatives without the usual trial-and-error approach, where each trial requires a separate analysis to identify the impact on control policies and expected cost.

To view the capacity-expansion results, we view the impact that different expansion alternatives (identified by x_3, x_4, and x_5) have on the expected cost of rationing and operations. Because the cost-to-go is a function of five state variables, it is difficult to view all possible combinations. Results are presented only for conditions of high initial storage levels (x_1 = 200 TAF and $x_2 = 500$ TAF) and low initial storage levels ($x_1 = x_2 = 0$).

The following results present the annual costs expected at the beginning of a 100-year time horizon using an inflation-corrected discount rate of 4%/yr. The higher a discount rate, the smaller the impact of future costs relative to current costs, and costs far in the future are diminished until they no longer matter. To indicate the impact of different discount rates, differences between results for 0 and 4% are mentioned in the following discussion.

5.1. Benefits of Groundwater Development

Figure 7 displays the expected annual cost of rationing and system operations as a function of pumping and recharge capacities, assuming high initial storage levels. At 4% the discounted accumulated costs for the entire operating horizon are a factor 25 times greater than the annual costs.

Table 2. Variables for Capacity Expansion of the Conjunctive-Use Model

Variable	Type	Definition	Minimum*	Maximum*
u_1	control	supply to users, per year	0	600
u_2	control	groundwater pumping, per year	0	x_3
u_3	control	groundwater recharge, per year	0	x_4
u_4	control	release downstream, per year	0	infinite
x_1	state	surface reservoir storage	0	x_5
x_2	state	subsurface reservoir storage	0	500
x_3	state	pumping capacity, per year	0	100
x_4	state	recharge capacity, per year	0	50
x_5	state	surface reservoir capacity	200	300
s_1	stochastic	inflow from streams	0	infinite

*Values are given in thousands of acre-feet (1 ac ft is 1234 m^3).

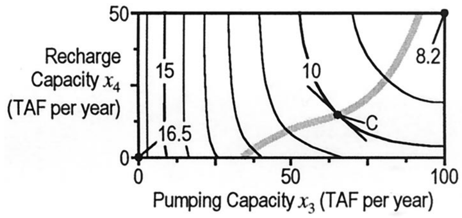

Figure 7. Expected annual cost (millions of dollars) for different levels of groundwater development with initially full reservoirs.

As capacities increase, the expected annual cost decreases from \$16.5 million to \$8.2 million, and the expected accumulated cost for the entire time horizon decreases from \$412 million to \$205 million (annual cost multiplied by 25). These results are for a surface storage capacity of 200 TAF (i.e., $x_5 = 0$); results for different surface storage capacities are similar in shape, only the magnitude of benefits changes (discussed in section 5.2 on conjunctive development).

Figure 7 can be used to balance the capital costs of pumping and recharge facilities (e.g., installing pumps, buying land, permitting, etc.) with their benefits (e.g., improved water supply reliability) to identify the best level of development and the best mix of pumping and recharge capacity. In practice, capital costs are highly variable and site specific. For the sake of illustration we assume that the marginal cost for expanding the pumping or recharge capacity is equal and constant. Total capital cost is represented by a straight line with a 45° slope, and the best mix of capacities is the tangent with a cost contour (e.g., point C in Figure 7). The shaded curve indicates the best mix of capacities for different levels of capital investment. The best level of capital investment matches marginal capital costs with marginal benefits.

The best mix of pumping and recharge capacity changes with the level of groundwater development. At low levels of development (i.e., low pumping capacity) the largest benefit is obtained by investing all capital in pumping capacity. Because reservoirs are initially full and because of the discount rate, it is possible to "mine" groundwater without concern for its replacement. At higher levels of development (or after groundwater levels have been depleted) some recharge capacity is required to replace the withdrawals. When development is moderate, a large pumping capacity can be used to meet severe shortages in a few years, while gradual recharge capacity can be used to replenish groundwater in most other years. When development is high, a significant recharge capacity is required. A high level of development requires a significant recharge capacity to replace withdrawals by capturing less-frequent flood waters.

5.2. Benefits of Conjunctive Development of Groundwater and Surface Water

Figure 8 displays the expected annual cost of rationing and system operations as a function of pumping and surface storage capacities. As capacities increase, the expected annual cost decreases from \$16.5 million to \$5.9 million, and the expected accumulated cost for the entire time horizon decreases from \$412 million to \$148 million. These results are for a recharge capacity of 50 TAF/yr; however, different capacities do not change the shape of the cost curves so long as some "sufficient" level of recharge is available. In Figure 7 the impact of limited recharge appears to influence results only at the highest pumping capacities (above 80 or 90 TAF/yr).

The straight-line cost contours result in a trade-off of capacities that favors the expansion of either pumping or surface storage but not both. As a result, a mix of surface storage and pumping capacity expansion is best only when the capital cost of a TAF of annual pumping capacity is the same as the capital cost of 3 TAF of surface storage capacity. The estimated cost for 100 TAF of surface storage is \$133 million, and the estimated cost for 100 TAF of annual (3.9 m^3/s) pumping capacity is \$1 million [*Fisher et al.*, 1995]. As a result, it appears that added pumping capacity should be favored over increased surface storage capacity. This supports the general observation of other authors that adding subsurface storage is significantly more cost-effective in improving the water supply reliability of many existing surface reservoir systems [*Fisher et al.*, 1995; *Lettenmaier and Burges*, 1979].

If we use a zero discount rate to develop control policies and a cost function, the expected accumulated costs and the benefits of capacity expansion are greater. A smaller discount rate produces larger long-term costs from rationing (and more frequent rationing), and the argument for subsurface storage becomes even stronger. Limits on pumping and recharge (combined with larger subsurface storage capacity) mean that groundwater is used to meet long-term demands, surface water is used to meet short-term demands, and a lower discount rate increases the value of satisfying long-term demands. For a zero discount rate, maximum development of surface storage capacity reduces the expected annual cost by \$4.8 million (\$17.8 million to \$13.0 million), and maximum development of groundwater reduces the expected annual cost by \$8.0 million (\$17.8 million to \$9.8 million). In contrast, the respective reductions for a 4% discount rate are \$4.4 million and \$8.3 million for high initial storage levels or \$4.4 million and \$5.7 million for low initial storage levels.

5.3. Impact of Initial Conditions on Results

When a discount rate is applied to future costs, initial conditions have a significant impact on expected costs. For the conjunctive-use model, expected costs are higher when reservoirs are initially empty (Figures 9 and 10) than when they are at the high levels used earlier (Figures 7 and 8). Note that the annual costs for the full development of groundwater, \$8.2 million when initially full and \$13.3 million when initially

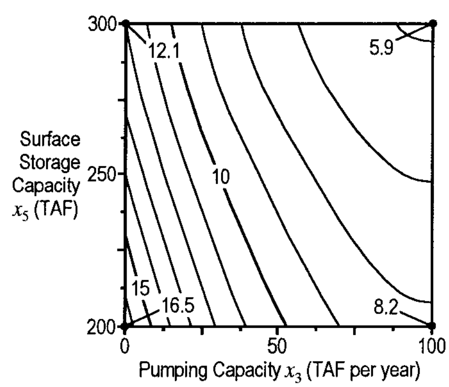

Figure 8. Expected annual cost (millions of dollars) for different levels of conjunctive development with initially full reservoirs.

empty, bracket the average annual cost-to-go in Figure 6 of $10 million.

As before, if the marginal costs for expanding pumping and recharge facilities are equal and constant, the shaded curve in Figure 9 identifies the optimum mix. Now the mix requires significant recharge capacity, especially at low levels of groundwater development. Without the ability to recharge, pumping capacity is worthless since it is not possible to mine groundwater. At high levels of groundwater development, initial storage levels become less significant, and the best mix approaches that of Figure 7.

Figure 10 displays the expected annual cost as a function of pumping and surface storage capacities, assuming that reservoirs are initially empty. The benefit of added pumping capacity is less because groundwater must be recharged before water is available for pumping. Nevertheless, adding subsurface storage capacity still appears to be more cost-effective than increasing surface storage capacity.

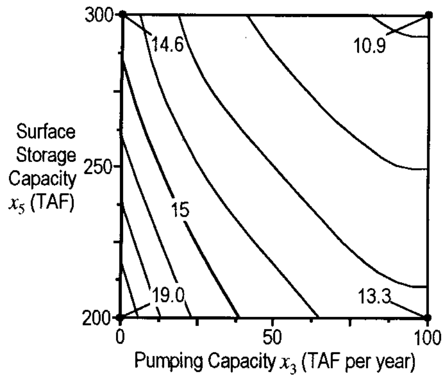

Figure 10. Expected annual cost (millions of dollars) for different levels of conjunctive development with initially empty reservoirs.

6. Summary and Conclusions

Management of conjunctive-use systems requires development of appropriate control policies and plans for capacity expansion. Control policies specify real-time operating decisions that ration water supplies to users and that allocate stored water between reservoirs. Plans identify the pumping, recharge, and surface storage capacities required to achieve a sufficient level of system reliability at minimum cost.

Both surface and subsurface storage are used to redistribute water in time to match supply to demand. However, surface and subsurface storage differ in storage capacity, recharge and depletion rates, and operating costs. As a result, surface storage is effective where rapid fluctuations in level are required to meet short-term demand (during the next season or year), and subsurface storage is effective where fluctuations in level are more gradual and are used to meet long-term water demand during a prolonged drought of several years.

Identification of appropriate control policies and capacity-expansion alternatives for systems that integrate surface and subsurface storage may be difficult and contentious, particularly when hedging is important. Identification of appropriate policies and plans is complicated by the unfamiliar interaction of these storage mechanisms. Systems analysis allows us to identify control policies and evaluate capacity-expansion alternatives using an objective approach.

As demonstrated by the conjunctive-use model, real-time control requires policies that consider complete state information, and simple rules may not be efficient. In particular, policies that ration (to balance the current benefits of water use with future benefits) and that allocate stored water (to maximize water supply reliability) must be flexible so that they can accurately identify when and how much to hedge. Gradient dynamic programming is especially useful in this regard since it can be used to accurately represent a control policy or cost-to-go function while mitigating the curse of dimensionality.

Analysis of the conjunctive-use model demonstrates that despite associated operating costs, control policies should make active use of pumping and recharge to meet demand and to allocate stored water. This appears to be particularly true when a system is approaching full utilization of its water resources. Thus it seems that optimal operation of pumping and recharge facilities may be in conflict with heuristic control policies based on some notions of "common sense." In particular, when groundwater levels are low, optimal policies pump less and recharge more, even if there are insufficient water supplies to meet all demands.

Analysis of the conjunctive-use model also demonstrates that dynamic programming methods can be used efficiently to evaluate the best mix of facilities in capacity expansion. Changes in the system configuration, inputs, or goals require identification of new control policies, and the methods presented allow an evaluation of these changes with simultaneous identification and application of optimal control policies. As a result, dynamic programming methods may be significantly better than trial-and-error methods for which the evaluation of proposed system configurations is separate from the identification of control policies.

Though the current model is simple, it can be modified to permit practical analysis of real systems. These modifications include shorter stages and additional state variables for other reservoirs and for water supply forecasts. Though these modifications would increase the computational effort required to solve the conjunctive-use problem, they are within the capabilities of the methods employed. In addition, managers and policy makers would need to accurately define the physical parameters and costs used in the model. Nevertheless, the current model captures important differences between surface and subsurface storage, and the results improve our understanding of effective conjunctive-use management.

Using a stochastic model with five state variables, we have identified the optimal policies for conjunctive-use operation and capacity expansion. A comparison of water supply benefits and the capital costs indicates that subsurface storage can improve water supply reliability in existing surface reservoir systems for less than one tenth of the cost of additional surface storage.

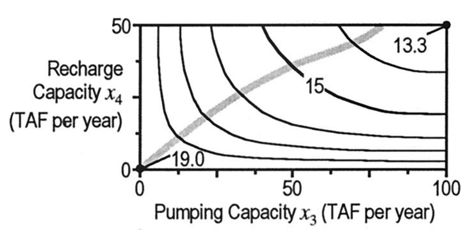

Figure 9. Expected annual cost (millions of dollars) for different levels of groundwater development with initially empty reservoirs.

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