Implicit Stochastic Optimization with Limited Foresight for Reservoir Systems

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Abstract

Reservoir operation has been described as a multistage stochastic control problem, yet solutions to an explicitly stochastic formulated multi-reservoir operation problem remain problematic. Despite development of new techniques, implicitly stochastic optimization (ISO) models solved using linear programming (LP) remain one of the most readily applicable to the analysis of complex systems. However the attribute of perfect foresight limits the immediate usefulness of such models and hinders the derivation of operating rules for subsequent testing in simulation models. This dissertation presents a modification to the traditional ISO model that overcomes the problem of perfect foresight and incorporates consideration of risk in the prescribed reservoir operation. The proposed method is implemented using sequential runs of an ISO model, where each run has an optimized terminal or carryover storage value function. The time horizon for each run is reduced to a fraction (1/n) of the period-of-analysis. The series of n linked consecutive runs form the optimal operating policy over the entire period-of-analysis. An iterative non-linear search algorithm is used to define the optimal carryover storage value function. Balancing rules are used to reduce the dimensionality of the multi-reservoir operation problem. The method is demonstrated using three case studies: single reservoir operation; single reservoir operation with conjunctive use of groundwater; and multi-reservoir operation. In all three cases the reservoir(s) have the dual purpose of flood control and water conservation. The objective function is to minimize the economic cost of shortage associated with downstream agricultural deliveries. A generalized network flow algorithm with gains is used to find the optimal solution.

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1. INTRODUCTION

For California, as well as the rest of the world, continued economic growth depends on a well-managed and reliable water supply. However, recent experience has shown that given present facilities, California can support neither existing nor projected levels of agricultural, urban and environmental water demand. Under current projected operation, the California Department of Water Resources (DWR) forecasts 2.9 maf in average year shortages by the year 2020 (DWR 1998). Without structural and non-structural changes to the State's water supply system and implementation of demand management, DWR predicts drought year shortages of 7.0 maf (DWR 1998). The driving force creating these levels of predicted shortage is the dramatic increase in the State's population. In 1999 the population of California increased by 540,000 to 33.8 million. The California Department of Finance predicts a population of 47.5 million by the year 2020. The rise in urban water use is matched by an increasing dedication of water for environmental purposes. The Central Valley Project Improvement Act[1] passed in 1992 dedicates 800,000 af of the federal Central Valley Project (CVP) yield for fish, wildlife and habitat restoration. The Act also calls for the doubling of anadromous fish in Central Valley streams and rivers. Take limits on the federally listed Delta Smelt potentially may reduce exports from the Sacramento-San Joaquin Delta to the San Joaquin Valley and Southern California. Water supplies will be further constrained by the implementation of the Colorado River Board 4.4 Plan that sets out the progressive reduction of Colorado deliveries from the current 5.3 maf/yr to the State's basic apportionment of 4.4 maf.

Supply-side solutions to the perceived water shortage focus either on the construction of new facilities or more efficient management of the existing system. The development of California's water infrastructure has been implemented by a mix of federal, state and private agencies. Despite the size of the CVP and the State Water Project (SWP), local agencies supply 70% of California's water (DWR 1998). Inevitably integrated operation is difficult to achieve, as the many agencies charged with managing the State's water supply have different objectives. However, despite difficulties, many of California's reservoirs are successfully co-managed. Integrated operation of CVP reservoirs increases hydropower production and water supply reliability (USBR 1992). Releases from CVP and SWP reservoirs are coordinated to meet water quality standards in the Sacramento-San Joaquin Delta (USBR and DWR 1982). USACE is currently studying whether integrated operations can improve flood control in the Central Valley (USACE 1999).

In addition to striving for improved integration, agencies are modifying reservoir operations that have evolved slowly over years to often rapidly changing objectives and perceived environmental needs. Low flow augmentation, water quality standards and water temperature concerns, as well as increased conjunctive use operations, require new reservoir operations.

[1] Title 34 of Public Law 102-575, Section 3406 (b)2

Improved water supply management and water conservation are methods of reducing water shortages. Water supply fluctuations can be diminished through increased system storage. While surface storage has long been out of favor with California voters, greater use of groundwater storage is advocated by many agencies and private parties (CALFED 1999, DWR 1998, NHI 1997 and 1999, USBR 1995). Water storage in aquifers for conjunctive use is especially attractive because it "results in less evaporation, has a lower capital cost, usually does not require an extensive distribution system, and is generally more environmentally acceptable than surface storage" DWR (1987, p47). However the use of groundwater storage is not without controversy. It has long been regarded as a resource for the sole use of overlying landowners. Its use as an integrated element in a regional or statewide supply system has met local resistance. However it is likely that conjunctive use of groundwater represents one of the most economic and environmentally benign methods of resolving the State's water problems (CALFED 1999).

In 1998 the State of California Resources Agency initiated a study at the University of California at Davis to explore structural and non-structural mechanisms to reduce water shortage and provide greater water supply reliability for urban, agricultural and environmental use. The study named "Quantitative Analysis of Finance Options for California's Future Water Supply" (more simply referred to as the "Capitalization" study) aimed to:

- Quantify the benefits of constructing new storage and conveyance facilities;
- Investigate the incentives of the private sector to finance these facilities; and
- Explore the role of water marketing and transfers in meeting demand.

Quantitative analysis was achieved through the development of an optimization model of California's inter-tied water system. The model, named CALVIN (CALifornia Value Integrated Network), represents a new development in water resources analysis for this region by its geographical extent, the integration of surface water and groundwater supplies, the choice of optimization over more traditional simulation models, and the use of economic drivers to allocate water rather than the existing system of water rights and contracts. The first stage of model development is described by Howitt et al. (1999).

Optimal reservoir operations in CALVIN are determined with full knowledge of all past and future model inflows. Perfect foresight arises through the use of deterministic optimization techniques combined with a single time series of inflow hydrology over which operations are optimized. This type of model, referred to as implicitly stochastic optimization (ISO), is relatively common in the academic literature (Young 1967, Bhaskar and Whitlach 1980, Karamouz and Houck 1982, Karamouz et al. 1992). Generalized operating rules have successfully been derived from model output and subsequently validated using simulation models. However, the attribute of perfect foresight causes unrealistic storage operations: large carryover storage prior to drought; and little storage prior to wet years. Perfect hedging of water supplies to minimize the economic impacts of water scarcity distorts both reservoir operation and reduces the economic valuation of existing and new facilities. This perfect foresight also hinders the subsequent deduction of operating rules. These rules may not be optimal given the stochastic nature of inflows and the inherent uncertainty of reservoir operating decisions.

The goal of many reservoir operations models is to develop reservoir operating rules to guide system operators. However groundwater resources are often excluded from these models. Where groundwater is included, its operation is often pre-determined independently and its presence not reflected in the formulation of surface reservoir operating rules. This may result in sub-optimal operating policies and performance.

This dissertation contains research work carried-out as part of the Capitalization study. It is divided into three main sections. The first section describes the optimization model, CALVIN. The second section focuses on limiting the perfect foresight that is an attribute of CALVIN and other similar deterministic optimization models. The last section considers how groundwater is best represented in what are predominantly surface water operations models. The goals of this dissertation are:

1) To demonstrate the impacts of perfect foresight on implicitly stochastic optimization model results.

2) To determine under what type of conditions perfect foresight results in substantial 'errors', (unrealistic storage operation, under-estimate of shortage costs and under-valuation of the benefits of new facilities).

3) To develop a method to partially eliminate perfect foresight, through the construction of a 'limited foresight' model with economically-derived values for carryover storage.

4) To use the limited foresight model to show how reservoir operation should be adapted in the presence of groundwater supplies to maximize economic benefits.

The limited foresight model described in this dissertation eliminates model foresight beyond the current water year. It is thus a better approximation of the decision process facing reservoir operators in the Western United States. In many watersheds, early spring measurements of the depth and water content of the snowpack provide reasonably accurate forecasts of reservoir inflow to the end of the water year. However, inflows for the following water year are largely independent of current and previous flows and therefore can best be represented in probabilistic terms. The limited foresight model uses network flow programming and an iterative technique to assign over-year or carryover storage that maximizes its expected value given the hydrologic uncertainty[2] beyond the end of the current water year. The model more correctly deserves the moniker of an implicitly stochastic optimization model, as though it uses a deterministic hydrologic time series it also captures the element of uncertainty. Groundwater resources and storage are readily included in the limited foresight model. Groundwater mining

[2] Some authors use the word "risk" where the probabilities of events are known and reserve the word "uncertainty" where the probabilities are not known. This convention is not followed here.

over the period-of-analysis is deterred using a system of penalties on over-year storage. The model can therefore be used to directly assess how management of reservoirs should be changed in the presence of groundwater supplies. The limited foresight model provides a direct economic valuation of surface water carryover storage.

This chapter has laid out the motivation and goals of the "Capitalization" study and the focus of the dissertation. **Chapter 2** describes the CALVIN model. **Chapter 3** reviews the problems of perfect foresight associated with the use of deterministic optimization models in the analysis of water resources problems. New techniques for determining optimal reservoir management are continually being published in the academic literature. Alternatives to the ISO approach are reviewed in detail. Explicitly stochastic and deterministic optimization approaches are compared and simulation is contrasted to common optimization techniques. The chapter subsequently describes the new limited foresight model. The use of the model is fully explored in this and the remaining chapters. In **Chapter 4** the limited foresight model is applied to analyze the operation of a single surface reservoir. **Chapter 5** extends the analysis to integrated multi-reservoir operation. Reservoir balancing rules are used to reduce the dimensionality of the problem. Methods of representing groundwater in optimization models are reviewed in **Chapter 6.** Using a simple single surface reservoir, single groundwater basin, **Chapter 7** shows how access to groundwater influences optimal surface reservoir operation and optimal levels of over-year or carryover storage. Finally **Chapter 8** provides some overall conclusions.

Economic optimization is usually based on minimizing the total economic costs due to water being a scarce resource. The terms "water shortage" and "water shortage costs" are easily misinterpreted. For the economist a shortage is the difference between demand at a given price and supply (excess demand). Under a perfect market shortages are due entirely to physical, legal or regulatory constraints. In this dissertation the term *shortage* is used for the difference between the (maximum) demand at zero price and actual delivery. Correspondingly s*hortage cost*, a function of shortage, is the area under the demand curve between actual deliveries and the maximum delivery at zero price (see Figure 1.1 below).

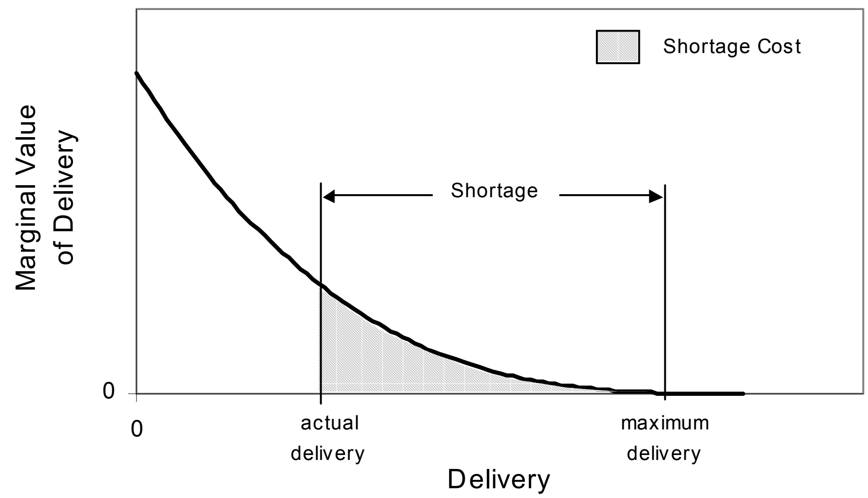

Figure 1.1 Definition of Shortage and Shortage Costs

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2. CALVIN: AN ECONOMIC-ENGINEERING OPTIMIZATION MODEL FOR CALIFORNIA WATER

Introduction

This chapter presents the development of an economic-engineering model for evaluating structural and non-structural water supply options for the State of California. The model, named CALVIN (California Value Integrated Network) operates water facilities and allocates water over the historical hydrology to maximize the economic value of agricultural and urban water use. Model details are described by Howitt et al. (1999) and related appendices. Geographically the model represents the majority of California's inter-tied water system, including the entire Central Valley, most the San Francisco Bay metropolitan area, and southern California. This relatively simple, if large-scale and detailed, optimization model supports several technical and policy conclusions with long-term significance for managing California's water.

Optimization

Simulation modeling has been applied practically to water resource systems since the early 1950s, and remains the mainstay for analysis of water systems. In contrast the use of optimization models for large-scale water resources planning is rare. An exception is its use by the World Bank as part of its investment studies (for example, World Bank 1993). During the 1980s there was much discussion among academic water resource modelers regarding why optimization models had been so little-used in practice (e.g. Rogers and Fiering 1986). Optimization is well documented in academic and research literature. Many authors have applied optimization techniques to parts of the California Central Valley Project (CVP) and the State Water Project (SWP). For example Hall and Shephard (1967) used a mixed LP-DP model to analyze storage operations in the Sacramento Valley. A diverse set of models have been developed and applied to power generation at CVP facilities (e.g. Becker and Yeh 1974, Marino and Mohammadi 1983 and 1984, Mohammadi and Marino 1984, Grygier and Stedinger 1985, Marino and Loaciciga 1985a and 1985b, Tejada-Guibert et al. 1990, and Johnson et al. 1991). Lefkoff and Kendall (1996) developed an optimization model for the SWP.

While CALVIN represents a new approach to modeling California's water system, it uses existing and previously used and well-tested computer programs as its core. The particular technique chosen for CALVIN is known as network flow programming (NFP), a subset of linear programming (Jensen and Barnes 1980). Other optimization techniques such as dynamic programming are not readily applicable to complex systems due to the computational burden. The use of NFP to develop reservoir operation guidelines is well established. Examples include the Texas Water Development Board studies (TWDB 1970), the Saskatchewan-Nelson basin studies (Kerr 1972), Trent River system studies (Sigvaldason 1976), surface water allocation model AL-V (TDWR 1981), the Lower Hunter water supply system (Kuczera 1989), the California State Water Project (Chung et al. 1989), the Oroville Complex studies (Sabet and Creel 1991), Alameda County, California (Randall et al.) and various applications of MODSIM (e.g. Frevert et al. 1994). However most of these studies use NFP to optimize reservoir operations over a single time step and are embedded within a simulation model.

An optimization model will set the value of all decision variables so as to maximize (or minimize) the value of the objective function subject to meeting all constraints. To apply an optimization model to a particular problem several questions need to be answered: what variables are to be optimized; what is the performance objective to be maximized or minimized; what constraints should be considered; and what models/mathematical solution techniques should be used? Performance measures for optimization are usually expressed in terms of economic benefits. General guidelines for economic evaluation are given by the Water Resources Council (1983). The general measurement standard is willingness-to-pay. As applied to this particular study, the performance objective is to maximize statewide economic benefits for agricultural and urban water use less operating costs. The decision variables to be optimized are the time-series of reservoir releases and water allocations. Constraints include the conservation of mass or continuity (inflow - outflow = change of storage), capacity limits of the system (storage, conveyance, and water treatment) and regulatory or policy requirements (minimum instream flows, restrictions on allocations and transfers etc.).

Optimization models differ from the more widely used simulation models in that they are not driven by a predetermined set of operating rules. Optimization models determine the *"best"* water allocations and operations given a set of economic values. In contrast, simulation models can be used to derive the economic benefits from a *given* a set of water allocations arising from a pre-defined set of reservoir operating rules. These two types of model should be used in conjunction. An optimization model requires many simplifying assumptions but can be used to quickly screen many alternatives. Detailed simulation modeling of promising alternatives is subsequently required to confirm the potential and refine or adjust promising solutions (Lund and Ferreira 1996).

Network Flow Programming

Network flow programming has long been used to help solve complex logistics problems in commercial and military areas. In water management, network flow programming has been used as part of some simulation models (Israel and Lund 1999). The California Department of Water Resources (DWR) simulation model for the State Water Project, DWRSIM, uses this technique to meet storage and delivery targets (Chung et al. 1989).

Network flow programming involves representing the system as an interconnected network of nodes and links. Nodes are divided into storage and non-storage nodes. Links represent possible flow paths between nodes. Applied to water resources systems storage nodes may represent either surface reservoirs or groundwater basins. Non-storage or junction nodes represent, points of diversion, return flow locations or other fixed-point features. For multi-period analysis, a set of identical networks is connected by links through time, one link for each storage node, and one network for each time step. Links through time represent carryover storage. To obtain a fully circulating network additional nodes and links are added to satisfy the overall mass balance. Networks-with-gains represent an extension of the pure network problem where coefficients applied to links are used to represent evaporation or other system losses.

To quantify an objective, costs are assigned to flows on links. These represent either real costs or more simply weights or priorities. Where the costs are non-zero, each unit of flow through the link will incur a penalty. Non-linear convex cost functions must be approximated as piecewise linear. The "cost" link between two nodes is replaced by a series of parallel arcs with upper and lower bounds on flow and unit costs defined by the interval and slope of the piecewise linear function. The links "*l*" in the objective function and constraints are replaced by the expanded set of arcs "*a*".

The objective function expressed in minimum cost network flow form is:

$$\text{Minimize} \sum_{t=1}^{T} \sum_{l \in L} c_{l,t} x_{l,t} \tag{1}$$

subject to:

$$\sum_{j \in o_i} x_{j,t} - \sum_{k \in I_i} g_{k,t} x_{k,t} = 0 \quad \text{for all } i \in N, \text{for all } t = 1,2...T \tag{2}$$

and:

$$l_{l,t} \le x_{l,t} \le u_{l,t} \quad \text{for all } l \in L, \text{for all } t = 1,2...T \tag{3}$$

where *c* is the unit cost or weighting factor per unit of flow in link or arc *l* during period t and x_{lt} is the flow rate at the upstream end of link *l* during period *t*. T is the total number of time steps and L is the total number of links and arcs. O_i is the set of all links originating at node I, I_i is the set of all links terminating at node I, g_{lt} is the flow gain across link l during period *t*, N is the set of all nodes in the network, l_{lt} is the lower bound on flow in link *l* and u_{lt} is the upper bound on flow in link *l*.

The network flow algorithm computes the value of flows in each link (or arc) for each time step that minimizes the objective function subject to the constraints of maintaining a mass balance at nodes and not violating user-specified upper and lower bound on flow through the links. The advantages of the network flow formulation is the gain in computational time when compared to the more generalized linear programming. Sun et al. (1995) found a generalized network solver to be 11-17 times faster than state-of-the-art revised simplex method. However network flow programming often requires greater simplification of the physical system being represented, as flow constraints cannot be related to other state variables in the network.

CALVIN Model Components

CALVIN has two principle components: a set of databases and a reservoir system optimization model. The optimization model is a generic network flow optimization program that is entirely data driven. All inputs that define its application to the California system are stored in the databases.

Databases

Input data for the optimization model consists of the network configuration or connectivity matrix for the California system, time-series (hydrologic inflows and time varying constraints), scalar values (fixed constraints – e.g., capacities, fixed costs and fractional gains and losses) and relational or paired data (functional relationships e.g., reservoir elevation-area-capacity, economic penalties). Time-series and paired data are stored using the HEC'S Data Storage System (HECDSS) which was developed specifically for water resource applications (USACE 1995a). All other input data is stored in a Microsoft Access© database. Within the Access database, tables define the properties associated with nodes and links within the network and pathnames to access data from DSS. Extensive documentation of the sources and quality of the data (metadata) also is included in the Access database.

Network Solver

The network solver used by CALVIN is HEC-PRM (Hydrologic Engineering Center-Prescriptive Reservoir Model). This generic model was developed by the US Army Corps of Engineer's Hydrologic Engineering Center (Davis and Burnham 1991, USACE 1999). Its purpose was to enhance the Corps reservoir analysis capability and provide an objective oriented model to evaluate reservoir operations. HEC-PRM supplements existing simulation models, such as HEC-5 (USACE 1982). Developed specifically to examine the economic operation of large hydropower systems, HEC-PRM can accept non-linear objective functions and computes hydropower benefits using successive linear approximation methods. Base on user-specified penalty functions of system performance, the model produces a time-series of flows and reservoir storage scenarios that optimize system operation. HEC-PRM has been successfully applied to the Missouri River, Columbia River, Central and South Florida, Tahoe-Truckee, and Alamo reservoir systems (USACE 1991a, 1991b, 1992a, 1992b, 1993, 1994a, 1994b, 1995b, 1996, 1998a, 1998b, 1998c; Lund and Ferreira 1996; Israel, 1996). Objectives in these studies have included flood control, hydropower, and water supply. However CALVIN represents a very substantial increase in the size of the system modeled using HEC-PRM. This has been made possible due to recent and continuing increases in computer processing speed.

Model Inputs

Figure 2.1 represents the flow of data through CALVIN. Model inputs can be divided into six categories: (1) network representation of California's rivers, reservoirs, aquifers, canals, aqueducts and demands; (2) surface water and groundwater inflow hydrology; (3) urban economic penalty functions; (4) agricultural economic penalty functions; (5) environmental flow requirements; (6) other policy and physical constraints. Separate economic models have been constructed to derive the urban and agricultural penalty functions.

Network Representation of California's Water

California's inter-connected water system has been represented by a network flow diagram of approximate 800 nodes and 1,700 links. Typical components are illustrated in

Figure 2.2. Associated with surface storage nodes are links representing boundary inflows, reservoir evaporation and reservoir releases. Associated with each groundwater storage node are links representing natural and artificial recharge, pumping, and regional groundwater movement. Junction nodes occur at specific facilities such as pumping, power or water treatment plants, or more commonly points of diversion points and points of confluence. Junction nodes also occur on the model boundary at 'external' inflow and outflow locations. Demand nodes represent some aggregation of agricultural, urban or environmental demand for water. They have a single inflow and a single outflow. For agricultural and urban demands the inflow link representing deliveries has an associated penalty function. Consumptive use at the node is represented by a gain factor of less than one on the downstream link. Water not consumptively used returns to the stream network or percolates to groundwater. Due to limitations imposed by network flow programming, agricultural demand has been split into two components: one component with return flow to groundwater, the other with return flow to the surface system.

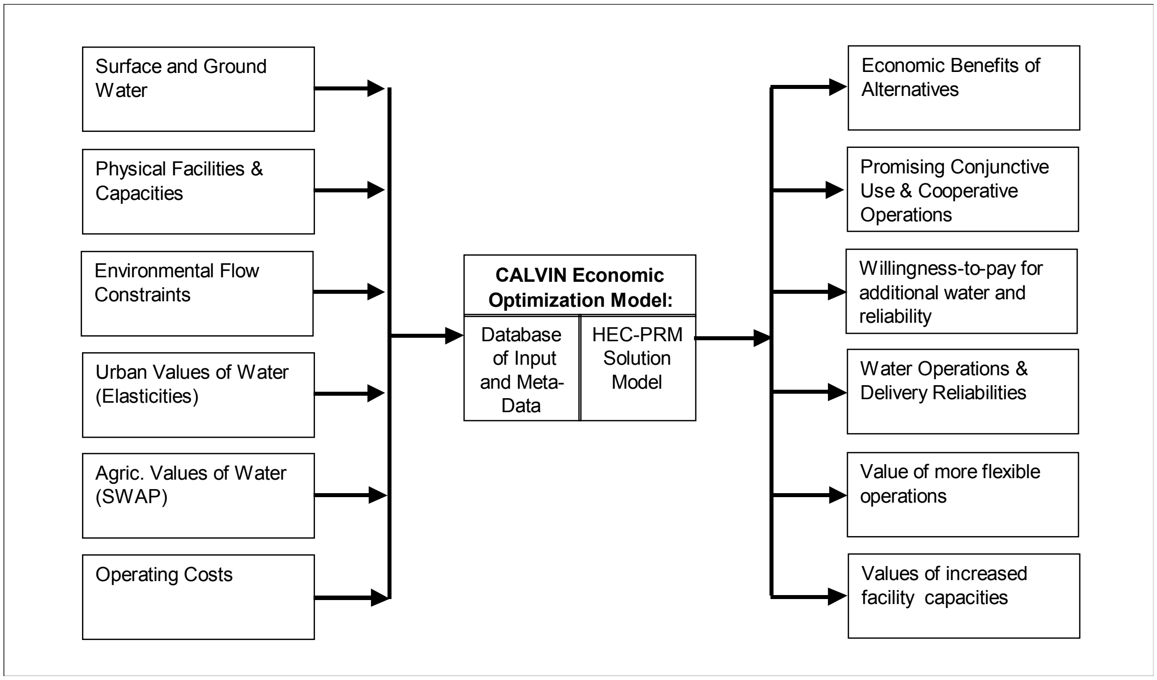

Figure 2.1 Data Flow for the CALVIN Model

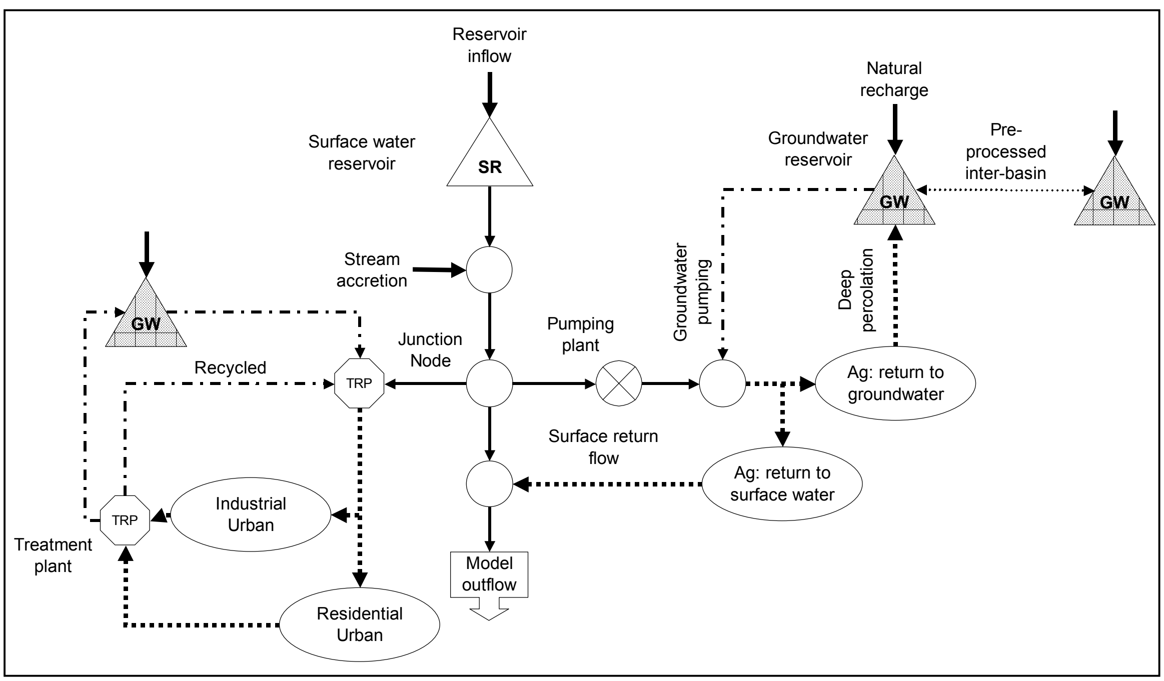

Figure 2.2 Example Network Diagram for CALVIN

Hydrology

CALVIN is a deterministic or implicitly stochastic optimization model. The input hydrology consists of a 72-year time series based on the historic record, October 1921 to September 1993. This period was chosen primarily due to the ready availability of data prepared for large-scale simulation models. The period also represents the extremes of California's weather. It includes the three most severe droughts on record: 1928-1934, 1976-1977, and 1987-1992 (DWR 1998). Given the observed persistence of drought phenomena and large geographical extent of the model involving numerous stream flows, alternate hydrologic approaches such as Monte Carlo analysis or explicit stochastic optimization are not considered practical.

Although CALVIN prescribes monthly operations over a 72-year period, it's demands and facilities are in some sense static. Demand is estimated from a static agricultural production model and a static urban demand model for year 2020 conditions. The time-varying hydrology can be viewed as representing the range of possible flows and their implicit spatial and temporal correlation structure. Results should therefore be expressed in terms of supply reliability rather than interpreted as a specific sequence of deliveries.

California's hydraulic infrastructure has progressively developed over the last 60 years. Land use changes have altered the amount and timing of runoff. On-stream storage and diversion of stream flows have modified the seasonal variation in stream flow. For flows originating upstream and outside of the modeled region, the historic flow is modified to reflect the stream flow that would have occurred with the current infrastructure in place, but with a projected operation and under a 2020 projected land use. This represents the flow that would occur if the historic pattern of precipitation were repeated. Flows that originate within the modeled area, either from direct runoff or stream-groundwater interaction, are based on a rainfall-runoff model and leakage rates across the streambed. Calibration flows have been added to the stream network to adjust these empirically calculated stream accretions to be consistent with gage data where possible.

Groundwater flows are divided into two categories. The first category consists of natural recharge from precipitation, lateral groundwater movement between groundwater basins, accretions from stream flow, and subsurface inflow from outside the model area. These flow components are pre-processed based on an assumed system operation and aggregated into a time series of fixed monthly inflows to each groundwater basin. The second component consists of groundwater pumping, recharge from irrigated agriculture and urban wastewater and artificial recharge (conjunctive use/groundwater banking). These components are represented explicitly in CALVIN and are determined dynamically.

Economic Penalty Functions and Variable Costs

Operations and allocations made by CALVIN are driven by economic values for agricultural and urban water use in different parts of the state. The economic values are based on users' willingness-to-pay. This is defined as the amount a rational informed buyer should be willing to pay for an additional unit (of water). Under a competitive, unregulated market the willingness-to-pay will equal the market price. The economic values are estimated using separate economic models for each water use sector. The economic value functions implicitly include the cost of water conservation measures by water users and the potential to substitute conservation for supplies.

Economic valuation can be applied to other system objectives. Hydropower is a significant contributor to the California water economy. The representation of flood damage penalties would allow the model to trade flood storage with water supply reliability. However time constraints have prevented these elements being represented in the current version of CALVIN.

No explicit economic value functions for environmental water needs are included since few, if any, credible statewide estimations of environmental value functions exist. While dollar values have been assigned to specific environmental benefits through contingent valuation techniques, these numbers have yet to be developed to levels of consensus comparable to agriculture and urban water demands (Colby 1990, Shabman and Stephenson 2000). Implicit valuation of environmental constraints can be derived from the sensitivity analysis when such constraints "bind' system operation. These values, however, reflect only the urban and agricultural water users' willingness-to-pay and not society's existence values and as such represent a lower bound on the environmental value of water.

The use of willingness-to-pay as a metric for capacity expansion is likely to overestimate the demand for new facilities. For example, new storage facilities represented in CALVIN will increase water supply and lead to lower prices and greater demand. In reality capital and operating costs of new facilities will be passed onto the consumer through a system of tariffs. Only if the municipality can practice perfect price discrimination will it be able to extract sufficient money from consumers to financially justify the new facility.

Statewide Agricultural Production Model (SWAP)

The Statewide Water and Agricultural Production model (SWAP) has been developed in parallel with CALVIN to quantify the economic value of agricultural water use (Howitt et al. 1999, Appendix A). It extends the work presented in the Central Valley Production Model (CVPM) that was developed as part of the CVPIA Programmatic Environmental Impact Statement (USBR 1997). SWAP uses much of the original data contained within CVPM. SWAP is an economic optimization model that maximizes farmer's returns from agricultural production subject to production and resource constraints. The wide range of agricultural inputs have been aggregated and simplified to just three: land, water and capital. The model captures the manner in which farmers adjust crop production when faced with changes in the price or availability of water. This reaction was observed during California's recent drought. Farmers can make three adjustments. The largest impact on water use is brought about by a reduction in cropped area, i.e., land fallowing. A second means of reducing water use is the adjustment of the cropping mix. Finally farmers can practice deficit irrigation to a limited extent or adopt more efficient water application technology.

Crop production in California is modeled using 24 model regions, 21 in the Central Valley and 3 for Southern California. For each region SWAP is run a total of eight times for different levels of water availability. The marginal value of water is imputed from the Lagrange multipliers or shadow prices associated with the different water resource constraint. Plotted against water availability they represent points on a continuous function. The integrated area under this derived demand function is the value of water used in agricultural production as a function of applied water. For CALVIN this relationship is approximated by a piecewise linear function. These value functions vary from region to region, reflecting the diversity of California agriculture and also vary from month to month indicating the temporal variation in the value of water.

Urban Demand Model

The development of urban penalty functions is described by Jenkins and Lund (Howitt et al. 1999, Appendix B). Urban areas are divided into industrial and residential demand nodes. The residential group amalgamates the commercial, and public (government) water use sectors. Maximum demands for the residential sector are based on the 2020 projected population levels and per current (1995) per capita use factors. Residential water use values are based on monthly residential water demand functions derived from published price elasticities of demand, observed retail prices (in 1995 dollars), and observed residential water usage. Commercial and public water usage, for which neither price elasticity estimates of demand nor other economic value data exist are treated as having zero elasticity and are added to the residential demand function. This composite residential demand function is then integrated to determine the costs (loss in consumer surplus) associated with delivery levels to the residential, commercial, and public sectors that are less than the 2020 target demand. Industrial water use values are derived from survey data on the value of lost production in different industries in California under hypothetical shortages (CUWA 1991). It was difficult to extrapolate demand functions beyond observed price and use levels.

Elasticity approaches, while conventional and feasible for application across California are very simple representations of fairly complex demand processes. For small urban areas deliveries are constrained to meet a fixed schedule of monthly demands.

Operating Costs

Unit operating costs represent the variable costs associated with the delivery system. Capital and administrative costs (fixed costs) are excluded. Operating costs include pumping of surface water and groundwater, groundwater recharge, wastewater discharge, and water quality treatment and consumer impacts.

Constraints

Physical, institutional, and environmental constraints all limit the way in which the system can be operated. All constraints must be represented as either an upper bound, lower bound or equality constraint on flow through a particular link during a particular time step. Constraints on reservoir storage include maximum storage levels to represent dam safety or flood control levels, minimum storage levels reflecting minimum operating level, or temperature, recreation and emergency storage requirements. Ending groundwater storage constraints limit the amount of groundwater mining over the period-of-analysis. Capacity constraints on conveyance links are expressed as a set of monthly upper bounds.

CALVIN represents an ideal water market limited only by the capacity of the physical infrastructure and environmental constraints. It allocates water according to willingness-to-pay. Additional "institutional" constraints can be added so that CALVIN meets current projected water deliveries and/or mimics current projected storage operation.

Model Output

Model output consists primarily of prescribed monthly time-series of flows (e.g., diversions, deliveries, releases and groundwater pumping) and volumes (e.g., storage and reservoir evaporation) that minimize costs over the 72-year period-of-analysis. This output can be post-processed to produce time-series of shortages and shortage costs to urban and agricultural users. The model provides additional economic output in terms of the value of the objective function, and a time series of Lagrange multipliers on binding flow constraints and marginal values of additional water supplies at each node. The objective gives the total minimized cost ('penalty') for a particular model run. This reflects the integrated value of all water allocation decisions represented in the model over the period-of-analysis. Lagrange multipliers represent the increase in the objective function performance given a unit relaxation of a constraint. Given that flow and storage are constrained by system capacities, the Lagrange multipliers identify directly the economic benefits of a unit expansion of those capacities. These benefits will vary with time. Alternatively they indicate the opportunity cost of meeting environmental or other policy/institutional constraints. Inspection of the Lagrange multipliers reveals critical operational or capacity constraints that warrant further investigation.

Given the scale of the model, the very large data requirements and its many simplifications, absolute values from a single model run should be treated with caution. CALVIN's strength lies in the comparative analysis of runs with different policy or capacity constraints. This comparison quantifies the relative benefits of new facilities and of alternative system management and operation.

Limitations of Approach

To develop an economically based water resources planning model for most of the State of California requires many simplifications. Limitations of CALVIN can be categorized into: limitations due to the simplified representation of the physical system and of the governing institutions; limitations due to the availability and accuracy of data; and finally limitations due to the chosen mathematical form of network flow programming. This last category is of more general interest and so some of the resulting limitations are described briefly below. Many of these limitations could be overcome through using a LP or QP solver.

Water Quality

Water quality is a crucial element in urban water supply. Water quality is represented in CALVIN by assigning different water treatment and consumer costs to different water sources. At the margin CALVIN allocates water to urban users by selecting the least cost water source – in addition to water treatment this may include pumping and opportunity costs. In practice, this decision process is complicated by the process of blending, whereby a water purveyor may blend lower quality supplies with those of higher quality to meet standards. Blending capability may depend on the amount of local supply, the desired use of water, and the specific constituent concentrations, parameters largely simplified or unrepresented in a network flow programming formulation. Complex water quality standards control operations within the Sacramento-San Joaquin Delta. Relationships between flow and water quality are highly non-linear. Standards can only therefore be approximately enforced based on pre-processing of assumed flows. Given the inherent relationship between water quality and quantity, CALVIN's representation of water quality remains a potentially serious limitation.

Perfect Foresight

Reservoir operation requires a sequence of decisions taken with imperfect knowledge of future hydrologic events. However deterministic models solve for a simultaneous rather than a contingent set of decisions. These models therefore have perfect foresight and are able to adjust reservoir operation in anticipation of flood or drought. This can result in unrealistic reservoir operation with large carryover storage prior to drought years and little carryover storage prior to a sequence of wet years. It also leads to an overvaluation of existing storage facilities and an under estimate of the value of new storage. For the surface supply system, foresight beyond 5-10 years may have little value as the recurrence of wet years fills reservoirs to capacity and precludes any more long-term hedging.

Results from CALVIN represent an upper bound to the potential economic benefits of a particular system configuration and set of constraints. The model can be run sequentially using a series of shorter time segments that together cover the full period-of-analysis. However this poses difficulties in specifying economic values for the carryover storage condition to prevent excessive drawdown of reservoirs. Despite the limitations of deterministic omniscient models, the derivation of operating rules from model results is well documented in the literature. In many cases, these rule have been successfully tested and confirmed in subsequent simulation modeling.

Network Flow Algorithm

Network flow solution algorithms offer advantages of efficiency and speed. However, the use of a network flow formulation for CALVIN limits the ability of the model to represent complex physical and environmental operating constraints. All constraints must be represented as pre-determined bounds on flow through a link. Constraints dependent on state variables must be pre-processed based on an assumed operation. Model output must subsequently be postprocessed to check that these constraints have not been violated under the prescribed model operation. Examples of such constraints are environmental restrictions that depend on other state variables within the system such as reservoir storage, and non-linear physical constraints, such as reservoir release capacities that are a function of head.

Simplified Representation of Groundwater

Groundwater is represented as a series of interconnected lumped parameter or single-cell basins. Many of the groundwater flow paths are pre-processed based on an assumed operation. These include regional lateral groundwater flow, recharge from stream flow and recharge from precipitation. The magnitude of these flow components is very approximate, based on empirical relationships and hydrologic balances. Storage rather than head is the state variable. Groundwater operation is nominally constrained by upper and lower bounds on storage, though for most basins the usable storage is extremely large. Pumping costs are determined assuming a fixed head based on piezometric for a base 2020 projected operation.

Monthly Time Step

A monthly time step is the commonly accepted standard for reservoir planning models. However system constraints and operations criteria may be based on finer time scales. For example water exported from the Sacramento-San Joaquin Delta is constrained by real time salinity levels. Peak flood flows averaged over one month may result in an over-estimate of the ability of reservoirs to capture flood peaks and an over-estimate of water available for export.

Conclusions

Recent developments in computing, data, and data management allow water managers to practically employ more extensive, detailed, and explicitly performance-based approaches to water supply planning. These new tools allow the exploration and analysis of new approaches to water management. It is fortunate that these technological and data developments have appeared at a time when the historical management of California's, and many other large region's, water resource systems have become ill-suited or acutely controversial with present and growing societal demands for water uses.

This chapter reviews the methods and approaches used to apply large-scale databases and economic-engineering optimization to California's water supply system. This economic-engineering optimization approach is an extension of similar exercises undertaken in recent years for river basins throughout the US.

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3. OPTIMIZATION AND RESERVOIR OPERATION

Introduction

Since the early 1960s simulation models have been used to help plan and manage complex water resources systems (Maas et al. 1962). Typically simulation models are used to evaluate the consequences of a set of decisions (what-if analysis) over a hydrologic period of interest. These decisions may include the construction or expansion of facilities, or changes in the regulatory, legal or contractual demands on the system. In a pure simulation model, reservoir releases are determined by a set of predetermined operating rules. Through a series of simulations these rules can be modified and improved until model results are judged acceptable.

Growing demands for water has resulted in calls for more efficient water use while increasing environmental awareness has led to greater scrutiny of proposed system expansion. In this context optimization models provide a valuable additional tool for planning purposes. They provide a means of rapidly screening alternate development proposals and suggesting promising new operations for meeting new objectives or changed constraints. The role of optimization models is to supplement rather than replace simulation modeling. Although powerful mathematical tools, optimization models have their limitations. To remain computationally tractable, optimization models usually must represent the system in a simplified manner (Loucks et al. 1981, p22; Mays and Tung 1992, p289). Consequently, "optimal" solutions may not be optimal. The use of a single value criterion has been criticized as leading to the "indiscriminate pursuit of optimality" (Rogers and Fiering 1986). Optimization reduces the range of system variables that need to be explored in greater detail using simulation. Together optimization and simulation allow investigations to focus on areas of promising benefits.

An important goal of the combined optimization-simulation approach has been the development of reservoir operating rules to aid reservoir management. Many alternatives may exist in the temporal and spatial allocation of water. Reservoir operation is further complicated under stress conditions when not all demands can be met and competing objectives must be balanced. Operating rules have often developed and evolved over time but are usually based on simulation model results. However before rules can be tested using simulation models, they must first be identified or defined. Optimization models help define this point of departure. Simulation models that have operating rules derived from optimization models are reported by Jacoby and Loucks (1972), Evenson and Mosely (1970), King and Everson (1972), Toebes and Rukvichai (1978), Bhaskar and Whitlach (1980), Karamouz et al. (1992), USACE (1994 and 1995). This chapter reviews commonly used modeling approaches and methods for determining optimal operation of single or multi-reservoir systems.

The Pursuit of Reservoir Operating Rules

The literature concerning the development of operating rules for water resource systems is extensive, particularly for water supplies. Various modeling approaches are described below.

Reservoir Operating Rules and Hedging

Reservoir operating rules guide release decisions. Good reservoir management therefore requires the creation of "a set of operation procedures, rules, schedules or plans that best meet a set of objectives" (USACE 1991c). "Rule curves" define ideal monthly or seasonal storage volumes. When conditions are not ideal, i.e., all demands on the system cannot be met, "rules of system operation" define what actions should be taken (Loucks and Sigvaldason 1982). Typically rule curves divide the reservoir into a set of horizontal pools (e.g. top of conservation pool) that may vary during the year but do not vary from year to year. Operating rules specify reservoir releases as a function of deviations from the ideal storage volume and other state variables such as hydrologic conditions.

The standard linear operating policy (SLOP) is an example of a very simple reservoir operating rule. The SLOP as presented by Loucks et al. (1981 pp138-152), is shown in Figure 3.1[3]. Reservoir release is specified as a function of the total water supply i.e. current storage plus projected inflows. If water supply is less than full demand, all water is released from storage. Water supplies in excess of demand water are held in storage until at maximum capacity the reservoir starts to spill.

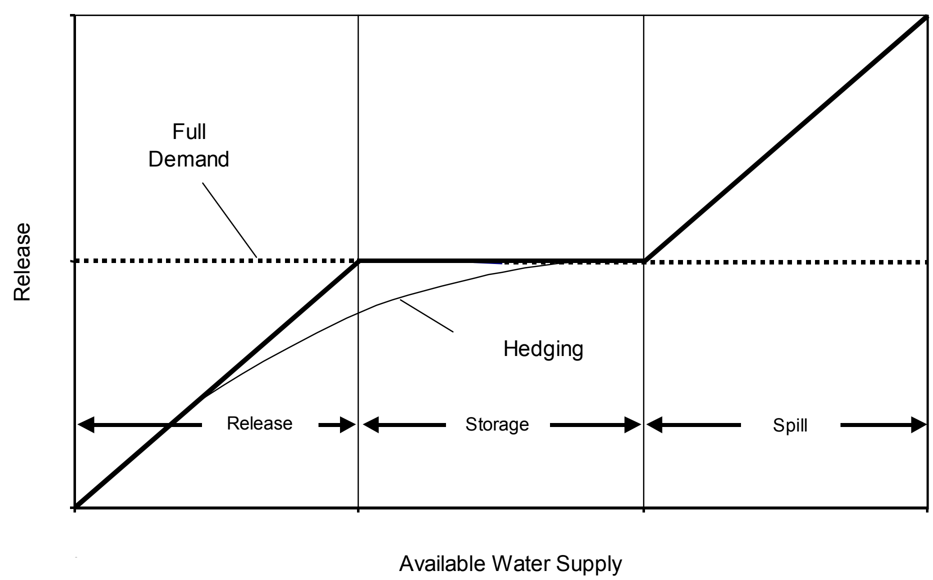

Figure 3.1 Standard Linear Operating Policy

Hedging rules curtail deliveries over some range of water supply to retain water in storage for use in later periods. This type of insurance is suitable for reservoirs with low refill potentials subject to variable annual inflows and operated for over-year storage. The effects of hedging have been investigated by several authors (e.g. Loucks et al. 1981, pp140-152, Hashimoto et al. 1982, Klemes 1977, Stedinger 1978, Moy et al. 1986, Bayazit and Unal 1990, Shih and Revelle 1993). Simple simulation models have shown

[3] The SLOP is referenced earlier by Maas et al (1962, pp293-297) and Fiering (1967, p11).

that hedging reduces the risk of large shortages but at the cost of having more frequent small shortages. Hashimoto et al. (1982) show that where the loss function (on releases) is linear, the SLOP is the best policy. They subsequently show that for hedging to be optimal requires a convex, non-linear loss function. Klemes (1977) found that an optimal policy converges to the standard policy with increasing hydrologic or economic uncertainty. To be optimal hedging requires not only that the loss function be convex and non-linear but also that the hydrology have substantial probability of persistence of dry periods. A hydrology that, perhaps oddly, has very severe droughts of one period followed by extremely wet conditions which always fill the reservoir, would never have hedging be optimal. Hedging requires the retention of water for carryover storage. Calculation of the optimal amount of carryover storage for hedging is difficult as it entails an assessment of risk.

Modeling Approaches

Reservoir operation is a multistage dynamic stochastic control problem (Marino and Loaiciga 1985). Reservoir operators often must make release decisions with incomplete information. Seasonal demand may be relatively fixed. In contrast, variation in natural streamflow between seasons may be highly variable. Long-range reservoir inflow forecasts are unreliable. Release policies for reservoirs with low refill probabilities and variable annual inflows may be oriented towards minimizing risk of losses in subsequent periods as well as maximizing short-term benefits. Various modeling approaches exist to treat the stochastic nature of streamflows. In a deterministic approach, inflows are based on the historic flow record or a sequence of synthetic data. A stochastic approach involves the assignment of probabilities to (usually) discrete flow ranges.

Deterministic Approach

Difficulties in explicitly stochastic formulations have led modelers of large integrated systems to rely on implicitly stochastic optimization (ISO) techniques (Labadie 1997). This class of deterministic models uses a long historic flow record or a synthetic streamflow sequence to represent the range and frequency of possible inflows. Large ISO models are readily solved using linear programming (LP) or network flow programming (NFP). For these techniques the increase in computation requirements with the dimensionality of the problem is relatively modest. Solution times are relatively fast, and standard code and generic computer models are readily available. Various decomposition techniques have been developed for complex systems having a large number of physical and operational constraints. Although ISO techniques are computationally simpler (Young 1967), the resulting “optimal” policies (release decisions) are unique to the assumed hydrologic time series. Repeated optimization for different synthetic flows may produce different optimal solutions unless the period-of-analysis is extremely long (Dembo 1991). Jettmar and Young (1974) and other authors have found that with flow records of between 60-80 years, the results of the rules from ISO are very good at optimizing the average system performance. Moreover optimal policies are determined using perfect information of all inflows over the period-of-analysis and so do not represent a realistic policy. Attempts to develop seasonal operating rules from model output have been the subject of several studies. Different techniques are reviewed by Lund (USACE 1994). Operating rules developed from policies prescribed from deterministic dynamic programming (DP) applied to single reservoirs are described by Young (1967), Jettmar and Young (1975), Bhaskar and Whitlatch (1980), Karamouz and Houck (1982), Karamouz et al. (1992). Except for Young, rules were subsequently evaluated using simulation. Lund and his colleagues developed seasonal operating rules from NFP models of multi-reservoir systems on the Missouri (USACE 1992b, 1994) and the Columbia (USACE 1995). Martin (1999) explored the use of genetic algorithms to 'automate' rule development from deterministic model output. Other techniques used to develop reservoir operating rules from deterministic optimization results include principal component analysis (Saad and Turgeon 1988, Saad et al. 1992) and artificial neural networks (Saad et al. 1994, Raman and Chandramouli 1996). More direct techniques to establishing operating rules, rather than their deduction from deterministic optimization results include stochastic dynamic programming (e.g., Hashimoto et al. 1982) and genetic algorithms (Oliveira and Loucks 1997). Despite the many advantages of the ISO formulation, the attribute of perfect foresight has limited its acceptability and application.

Stochastic Approach

Reservoir operation planning is inherently stochastic given the uncertain nature of reservoir inflows. Modeling risk is discussed by many authors (e.g. Hashimoto et al. 1982, Fiering 1982). However it is often inadequately represented in optimization models (Watkins and McKinney 1997). Deterministic models, which cannot directly represent future uncertainty, therefore seem to be inappropriate. Conceptually the approach taken by Marino and Loaciciga (1985a and 1985b) is the most satisfying. Optimal release decisions for the water year are determined each month on the basis of current state variables and forecasted inflows. The optimal release policy is followed for one month. Forecasted inflows are subsequently replaced with actual (historic) realized flows and the forecast updated. A new optimal release is determined and the process repeated. Although explicit stochastic optimization techniques may seem more germane (Yeh 1985; Reznicek and Cheng 1991), their application in practice presents considerable difficulties. Stochastic hydrology still poses many theoretical difficulties (Klemes 1974; Jackson 1975); for large systems it entails calculation of auto- and cross-correlation coefficients, and inflows must be modeled using one of only a few available statistical models (Loucks et al. 1981, p277-319). Stochastic analysis presents computational difficulties for both LP and DP. Three different stochastic techniques are commonly used in conjunction with first-order Markov chains: LP; DP; and policy iteration. Howard (1960) gives an excellent introduction to policy iteration. These techniques are compared by Loucks and Falkson (1970). Gablinger and Loucks (1970) found DP to be less computationally burdensome, however the number of state variables using traditional stochastic DP (SDP) methods is limited to two or three. Unfortunately, many of the iterative schemes that have been developed to reduce the dimensionality of deterministic DP problems are not applicable to their stochastic counterpart (Yakowitz 1982). The 'optimal' end-of-year storages can be determined by solving a multi-period explicitly stochastic LP or DP (see for example Hashimoto et al. 1982, Georgakakos and Marks 1989, Kelman et al. 1990). The steady-state optimal policy of a stochastic DP can be used to determine an optimal release policy. However the computational effort required makes this approach infeasible for complex systems.

Linear Decision Rules

Operating rules are commonly deduced indirectly from model results. Rules are more readily developed from explicitly stochastic models as they are not influenced by perfect foresight. An alternate but direct approach is to simplify operating rules so that they may be formulated as linear functions of state and past decision variables. Deliveries, storage, instream flows and other objectives can be expressed in terms of the parameters of a set of linear decision rules (LDRs) and solved for directly using mathematical programming techniques. Since the introduction of LDRs by ReVelle et al. (1969), they have remained a popular research topic and when used in conjunction with chance-constrained reliability models offer the promise of a screening model for both reservoir sizing and optimal operation. Various LDRs have been proposed: S-type where release is a function of storage (ReVelle et al. 1969; ReVelle 2000); SQ-type where release is a function of storage and inflow during the current time step (Loucks 1970); and K-type where release is a function of previous inflows and release decisions (McKee 1985). Early work by Young (1967) suggested that LDRs might be as effective as more complex (non-linear) rules. Many papers published in the 1970s and early 1980s extended the single reservoir model of ReVelle et al. (1969). Gundelack and ReVelle (1975) formulated a more general model. Joeres et al. (1971), Nayak and Arora (1971), and LeClerc and Marks (1973) applied LDRs to multi-reservoir systems. Monthly inflows were considered serially and spatially independent random variables and reservoir operations were solved assuming a cyclic annual operation within an infinite time horizon. Joeres et al. (1981) considered the problem of correlated inflows. Houck et al. (1980) used economic criteria to assess the performance of linear decision rules. Non-linear decision rules have been studied by Colorni and Fronza (1976) and Simonovic and Marino (1980). Loucks and Dorfman (1975) in evaluating various LDRs found them useful as preliminary screening models to demonstrate the trade-off between storage capacity and reliability but warn that detailed simulation modeling is required to determine final reservoir capacities or operating policies.

The interest in LDRs seems curious given their simplistic nature. Unless extended as a piecewise linear approximation of a non-linear function they suggest constant returns to water. Stedinger (1984) concluded that LDRs have little to offer except their simplicity. For a single reservoir operated for water supply, recreation and flood control, Stedinger reports that the SLOP out-performs LDRs (using total water shortage as a metric). For reservoir sizing Stedinger found that S and SQ type LDRs over-estimate the required capacity for a given reliability; S-type rules performing particularly badly. LeClerc and Marks (1973) concluded that chance-constrained LP has serious drawbacks for the design and analysis of large reservoir networks. The method does not define the magnitude by which the system fails. Highly non-linear economic objectives are unlikely to be well served by LDRs.

Genetic Algorithms

There have been several recent attempts to apply genetic algorithms (GAs) to the problem of deterministic reservoir operation (Oliveira and Loucks 1997, Wardlaw and Sharif 1999, Cai et al. 2001). GAs use a heuristic technique to explore feasible solutions to a problem and iteratively improve on the solution. The method is not impeded by non-linearities and is relatively easily applied to large complex systems. One of the advantages of the GAs is the identification of alternative near optimal solutions. Oliveira and Loucks (1997) used a GA to derive parameters for optimal reservoir operating policies. Solution "fitness" was evaluated using simulation.

Inflow Hydrology

This section reviews approaches to streamflow modeling in reservoir operation studies. It assumes that the decision has been made to use mathematical programming to aid subsequent simulation modeling. The purpose of the modeling activity is to determine suitable operating rules with particular emphasis on rules for over-year rather than within-year storage operations. As a starting point it is assumed that the historic flow record is available, albeit disappointingly short. The initial choice presented to model developers is whether to use the historic flow record: (a) as a deterministic time-series of reservoir inflows; (b) to generate a set of synthetic streamflow sequences for a deterministic Monte-Carlo model; or (c) to derive statistical parameters of the underlying population of streamflows to develop a stochastic model of reservoir inflows. The first approach is obviously the simplest and easiest to explain. The approach does, however, depend on the flow record being sufficiently long and climatologically representative. Traditionally, reservoir design and operation has been treated as a worst-case deterministic rule (Roefs and Bodin 1970) based on a critical hydrologic period. Use of this critical period for reservoir design and operation studies is reviewed by Hall et al. (1969). It is predicated on the assumption that the recurrence interval of the critical period is approximately equal to the length of record. Operations based on the critical period lead to very conservative reservoir management only suitable for very risk adverse decision makers. For general operation studies the entire record is used. It is extremely unlikely that the historic flow record will repeat itself. This approach can therefore be conceptualized as answering the question "with hindsight what would have been the best reservoir operation?" If the flow record is sufficiently long, possibly having been extended using longer precipitation records, it provides a good representative sample of the population of streamflows and represents the range and frequency of hydrologic conditions that could occur in the future. Model results should therefore be expressed in the form of reliability plots rather than a time series of deliveries. In this case it is usual practice to remove the effects of changes in land use, changes in upstream diversions and upstream storage regulations that impact streamflow during the period-of-record. The disadvantage of this approach is that reservoir releases and operating rules are determined from a single time series of flows. It is difficult to check the robustness of the prescribed policy to events more extreme than witnessed during the historic record. An extreme check might include reliability modeling based on two short historical droughts placed back-to-back. Despite disadvantages, this deterministic approach is used in the majority of simulation models (e.g., Chung et al. 1986) and in many early applications of optimization models described in the literature (e.g., Hall and his colleagues 1961, 1963, 1967, 1968). More recently this approach has been used to suggest optimal release policies for reservoir systems on the Columbia (USACE 1991a), on the Missouri (USACE 1991b), in Arizona (USACE 1998a), in Florida (USACE 1998b), Panama (USACE 1999) and in California (Howitt et al. 1999).

Several authors have tried to overcome the limitation of using a single hydrologic sequence for reservoir operations through the use of synthetic hydrology and Monte-Carlo analysis. Synthetic hydrology has been used to generate multiple possible realizations of streamflows from assumed population statistical properties estimated from the observed data. If the length of the synthetic flow record is set equal to the life of the project being analyzed, the range of plausible hydrologic scenarios can be examined (Burges 1979). Results from multiple runs can be used to assess the robustness of a proposed operating rule or the probability density function of benefits (or costs). Computationally this approach is similar, although more time-consuming, to use of the historic flow record, except the greater number of flow records allows more extreme events to be considered. The question is whether reservoir operations based on synthetic streamflow sequences are superior to those obtained using the historic record. Most of the literature on the use of synthetic hydrology is directed towards reservoir design rather than operations. Due to limited computer storage and high costs, early investigations considered very few synthetic traces. Young (1967) used synthetic hydrology with a backward-looking deterministic DP to derive annual operating rules for a single reservoir under a quadratic two-sided loss function. Jettmar and Young (1974) compared the use of historical records with synthetic records and found that the resulting operating rules tended to converge with about 70 years of record; other authors have also reported this result. Bhaskar and Whitlach (1980) used a similar approach to Young (1967) to develop monthly operating rules for a single reservoir under both one-sided and two-sided loss functions. Synthetic streamflows were generated using a lag-1 Markov model. The underlying distribution was assumed to be lognormal. The principle obstacle in applying this approach is developing a suitable hydrologic model of streamflows. Techniques for the synthesis of monthly streamflows have been developed by Beard (1965) and Fiering (1967). Multivariate models have been proposed by Fiering (1964), Matalas (1967), Valencia and Schaake (1973). Temporal disaggregation models (annual to monthly or seasonal) are developed by Meijia and Rouselle (1976) and Lane (1979), Stedinger et al. (1985). Thomas-Fiering or lag-1 Markov models are appropriate where there is little or no evidence of long-term persistence or memory. Markovic (1965) showed the two-parameter lognormal distribution to be well suited to annual streamflow volumes in the western US. From 1922-93, California experienced three droughts, two of six-year duration. This observed persistence of dry years is probably impossible to statistically represent without a greater understanding of large-scale climate processes. Hurst (1951) was the first to systematically investigate long-term persistence in the hydrologic record. First-order serial correlation models inadequately explain the Hurst phenomena (Fiering 1976). Various long-term memory models have been developed; multiple-lag autoregressive models (Fiering 1967), fractional gaussian noise models (Mandelbrot and Van Ness 1968), and broken line models (Meija et al. 1972). However Klemes et al. (1981) conclude that their use in preference to short-term models is not justified; impacts on reservoir design and operation are small compared with the accuracy and availability of economic and hydrologic data. The authors conclude that the "replacement of a short-memory streamflow model with a long-memory one amounts to the incorporation of a small safety factor into the reservoir performance reliability."

Often the historic record is too short to reliably fit more complex models (e.g. multi-lag AR models, ARMA models). Jackson (1975) describes three types of errors: (a) measurement errors; (b) sampling errors; and (c) errors due to inadequate models of complex natural phenomena. Many authors have discussed the importance of choosing the correct stochastic streamflow model in reservoir design (e.g. Fiering 1967; Askew et al. 1971; Hirsch 1979; Klemes et al. 1981). Jackson recommends that hydrologic models be as simple as possible but retain the capability of testing the affect of parameter values (e.g., mean, variance, serial correlation, persistence) on model outcome through sensitivity analysis. Stedinger and Taylor (1982a, 1982b) showed that the impact of parameter uncertainty to be greater than the impact of model choice. The hydrologic model should be appropriate to the decision problem. For example, the persistence of annual droughts is important in the determination of rules governing carryover storage but not for rules governing within-year operations. The large sampling errors associated with stochastic streamflow analysis creates uncertainty in the results (Loucks et al. 1981, Appendix 3c). There is no readily available method to test their reliability.

Jackson (1975) provides a good example of possible sampling errors[4]. She developed 100 sequences of synthetic streamflows, each 50 years in length, from a two-season variation of the Thomas-Fiering model. She subsequently estimated population parameters from each synthetic sequence and compared them to the values used to generate the sequence. The serial correlation coefficient was found to be highly unstable, with a range of –0.147 to 0.469. Linsley, Kohler and Paulus (1982, p404-405) illustrate the impact of different hydrologic models on reservoir operations. Reliability is shown to be significantly affected by the coefficient of variation, the skew, the lag-1 correlation and the memory of the assumed inflows. However for reservoir design, Vogel and Stedinger (1988) showed that the Monte Carlo approach reduced sampling error and led to more precise results than relying solely on the historic record. A variant in the use of a deterministic time series of inflows is the class of models that use forecasts and feedback control. This class of models is closer to representing real-time operations but the models are based on a monthly time-step that keeps them in the planning domain. Where streamflow forecasts can be assumed to be error-free, use of a deterministic optimization approach seems appropriate (Grygier and Stedinger 1985). However on a monthly time-step, forecasts are rarely perfect so that an adaptive deterministic approach is used. At every time-step a forecast is made. The forecast is treated as a deterministic input and an optimal release policy determined. The policy is implemented for only the current time step. The actual streamflow is then observed, forecasts updated and a new release policy determined for the next time step. Thus reservoir operations are solved as a series of sequential deterministic problems. Examples of such models are reported by Stedinger et

[4] The historic observed record represents one set of possible realizations of a random variable with an unknown distribution. Sampling error refers to the error in estimating the parameters of the unknown distribution from the historic data.

al. (1984) and Marino and Loaiciga (1985a). Depending on the complexity of the system different variants of DP have been used to solve the deterministic multi-stage problem. This type of adaptive approach has been called naive feedback control (Kelman et al. 1990). The optimal policy assumes forecasts are accurate, so ignores the inherent risk. The validity of this adaptive deterministic approach depends on the certainty equivalence controller principle (also sometimes referred to as the open-loop feedback controller). Marino and Loaicigo (1985a) point out that the value of the objective function obtained using CEC is less than obtained using perfect foresight but better than schemes that do not allow updating. Philbrick and Kitanidis (1999) discuss various aspects of certainty equivalent systems. A system is certainty equivalent when optimal policies can be determined based on expected value forecasts. This requires: (a) quadratic benefit\cost functions; (b) linear system dynamics; (c) no inequality constraints; (d) independent and normally distributed inflows. When a reservoir system is certainty equivalent, deterministic optimization can be used to identify optimal releases (Philbrick and Kitanidas 1999).

The final approach to modeling streamflow is the development of a stochastic hydrology. Explicit stochastic models use probability distributions of streamflow rather than sample realizations generated using synthetic techniques. Compared to Monte-Carlo analysis this requires two further simplifications: computational feasibility requires discretization of the probability data; and secondly relatively simple stochastic models must be used (e.g., lag-1 Markov model) to keep the dimensionality of the problem manageable. Each serial lag coefficient introduces a new state variable in a DP problem. The application of SDP to reservoir design and management is well documented in the water resources literature (e.g., Stedinger et al. 1984; Trezos and Yeh 1987; Kelman et al. 1990). For the majority of reported applications, optimization is with respect to the expected value of the objective function. Annual, seasonal and monthly models have been developed. Streamflows are usually represented using a lag-1 autoregressive or multivariate model. Coefficients may be estimated using the method of moments or maximum likelihood.

Various authors have used SDP to derive values (and thus implied operating rules) for end-of-period storage. The value function derived from a multi-period SDP model run to steady-state represents the expected benefits (or costs) of future system operation (see for example Georgakakos and Marks 1989, Kelman et al. 1990). Druce (1990) calculated the value of stored water for a reservoir in the British Columbia Hydro and Power Authority system. Turgeon (1980) obtained values of stored water in two reservoirs. Johnson et al. (1991) developed end-of-period values for power generation in California's Central Valley Project.

An interesting mixed deterministic-stochastic algorithm is reported by Kelman et al. (1990). This variation of SDP, known as sampling stochastic dynamic programming (SSDP), overcomes the computational difficulties of the traditional SDP approach by representing the stochasticity of streamflow explicitly. Reservoir operation is based on a large number of synthetically generated streamflows representing possible streamflow sequences. SSDP determines optimal release decisions by considering all "streamflow scenes" simultaneously. For a single streamflow scenario, SSDP reduces to a deterministic model solved with perfect foresight.

In conclusion, while deterministic models may be perceived as unsuitable, there remains no viable alternative for complex hydrologic systems. The computational inconvenience, streamflow probability specification, and difficulty of lay comprehension are likely to remain problematic, especially for large systems. Studies on reservoir design have shown that through reducing sampling error, synthetic hydrologic models provide results with a smaller confidence range than use of the hydrologic record, even when the 'wrong' hydrologic model is used to fit the data (Vogel and Stedinger 1988). However this approach for operational planning would require numerous models, and so is regarded as impractical. In the near future, despite its imperfections, the "unimpaired" historic flow record is likely to remain the hydrology of choice for most planning models.

There is perhaps some trade-off between the spatial representation of the system and its stochastic representation. Deterministic models allow more detailed spatial representation, but perhaps not as good a representation of hydrologic uncertainty. For explicitly stochastic modeling, 4 reservoirs is large-scale; for deterministic modeling 50+ reservoirs is large-scale.

Optimization Techniques

Linear Programming

Early applications of optimization techniques were often focused on the problem of reservoir design rather than operation. However optimum operation is implicitly embedded within the design problem. In many cases reservoir operation problems can be solved using either LP or DP. Among the available optimization techniques, linear programming is the most popular (Yeh 1985). It is applicable to problems in which the relations between variables are linear, both in the constraints and in the objective function to be maximized. Linear programming was first developed by economists in the 1930s concerned with the optimal allocation of scarce resources. Dantzig formulated the general LP problem and devised the simplex method of solution in 1947. Faster interior-point algorithms were devised in the 1980s for solving huge LP problems beyond the scope of the simplex method (Karmarkov 1984, Hillier and Lieberman 2001, p163). Standard LP algorithms and computer code are available for the solution of problems expressed in the standard form. Special computationally efficient algorithms are available for certain restricted forms of LP problems such as network flow programming, which have been popular for analyzing water resource systems. Post-optimality analysis is facilitated by inspection of the Lagrange multipliers and by parametric linear programming. Many reservoir problems can be realistically represented by a linear objective function and a set of linear constraints. Solution without recourse to binary integer programming requires that cost (benefit) functions be convex (concave). Various linearization techniques have been used to deal with non-linearities. However the strict linear form does significantly limit its applicability. Computation time is roughly proportional to the cube of the number of functional constraints but is much less sensitive to the number of decision variables[5] (Hillier and Lieberman 2001, p161). The number of functional constraints increases linearly with the number of periods to be analyzed (a continuity equation is required for each node for each time step). Given the limitations of computing power in the 1960s, decomposition techniques were developed for the analysis of a water resource system under a long sequence of inflows or time steps. The aim of these decomposition techniques is to replace the original problem in which the number of computations increases proportional to the power of 2m, where m is the number of constraints to fewer problems whose computations increase either linearly or quadratically. Dorfman (1962) illustrates the use of the decomposition principle developed by Dantzig and Wolfe (1960) to solve a multi-period reservoir operation problem. Benders decomposition (Benders 1962; Geoffrion 1972) has been applied for solving complex hydropower systems (Jacobs et al. 1995). Other approaches to overcome the problem of dimensionality include combined LP-DP techniques (e.g., Hall and Shephard 1967; Becker and Yeh 1974; Marino and Mohammadi 1983) and the use of restricted network flow forms of LP (e.g., Brendecke et al. 1989; Sun et al. 1995, Khaliquzzaman and Chander 1997; Lund and Ferreira 1996).

Dynamic Programming

Dynamic Programming (DP) has been described as the theory of multi-stage (sequential) decision processes (Bellman 1957). Although popularized by Belman in his 1957 work, the underlying techniques were first suggested by the Frenchman Massé in his analysis of hydropower production from a single reservoir (Massé 1946). Belman later described the name "dynamic programming" as misleading (N. Bellman 1989). DP is not a precise mathematical algorithm but a general approach of solving optimization problems. Consequently there are few, if any, generic DP programs that are available to solve specific water resources problems[6]. A problem formulated as a dynamic problem has several defining characteristics (Hillier and Lieberman 2001, p538; USACE 1991c, p64): the division of the problem into a series of stages that require a decision at each stage; a set of state variables that describe the system condition at the beginning of the stage; and a set of decision variables that transform the current state to the state at the start of the following stage. In this manner a highly complex problem is effectively decomposed into a series of sub-problems that are solved recursively. The validity of this approach rests on the "principle of optimality" (Bellman 1957): the probability of any future outcome is independent of the past event(s) and depends only on the present state. Given the current state, an optimal policy for the remaining stages is independent of the policy decisions adopted in the previous stages[7]. Since DP is based on a decomposition technique, it requires separability and monotonicity of the objective function (Rao 1996, p620). The problem must be expressed as the sum or product of functions for each stage.

Surprisingly the application of SDP to reservoir operation (Massé 1946; Little 1955) predates deterministic applications by over a decade (Yakowitz 1982), though

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[5] Based on the revised simplex method, solution times increase with the number of decision variables at a power of less than one.

[6] An exception is the generalized dynamic programming package CSUDP developed at Colorado State University.

[7] This is known as a Markovian property.

computational difficulties restricted the extension of SDP to multi-reservoir systems until the 1970s. The first English publication of the use of deterministic DP in a water resources context was in 1961 (Hall and Buras 1961). Since then there have been numerous studies applying DP to reservoir operation. Esogbue (1975) found that the use of DP was second only to simulation in water resource systems analysis literature. The popularity of the technique is ascribed to the fact that both the non-linear and stochastic nature of water resources problems can be readily represented by a DP formulation (Yeh 1985). Dynamic programming can handle non-convex, nonlinear, discontinuous objective and constraint functions. However, where the objective function can be linearized, discrete DP offers few advantages over LP. DP is generally better suited to stochastic inputs compared to other methods. A very large number of sequential-decision variables results in only a linear increase in computational effort.

A major impediment to the application of DP to multi-reservoir systems is the well-publicized "curse of dimensionality" (Bellman 1961). This describes the exponential growth in computation time with the number of discretized decision and state variables. In the academic literature there have been substantial advances in numerical techniques to reduce the dimensionality of large complex problems. These have allowed systems of up to10-17 reservoirs to be analyzed (e.g., Archibald et al. 1997). These new techniques include state increment dynamic programming (Larson 1968), differential dynamic programming (Jacobson and Mayne 1970), and imbedded state space dynamic programming (Morin and Esogbue 1974). Despite these numerical advances it has been suggested (Esogbue 1975) that poor communication between theoreticians and practitioners has resulted in many of these more advanced techniques being ignored. All methods of dimensionality reduction involve decomposition into sub-systems and the use of iterative procedures (Yeh 1985). DP models are attractive for analysis of multi-reservoir systems where the objective function cannot be linearized. The majority of applications described in the literature prescribe releases to maximize hydropower revenues (e.g., Hall et al. 1969; Heidari et al. 1971; Fults and Hancock 1972; Trott and Yeh 1973; Larson and Keckler 1969; Larson and Korsak 1970; Yeh et al. 1978; Turgeon 1981 and 1982). SDP has been applied to many simple systems in the academic literature. Operating rules developed from SDP models are described by Little (1955), Gessford and Karlin (1958), Butcher (1971), Schweig and Cole (1968), Stedinger et al. (1984), Trezos and Yeh (1987), Kelman et al. (1990), Karamouz and Vasiliadis (1992), Vasiliadis and Karamouz (1994), Tejada-Guibert et al. (1995).

Aggregation-Disaggregation Methods

Various aggregation-disaggregation techniques have been developed to reduce the computational burden of SDP. Turgeon (1980 and 1981) proposed decomposition methods for reservoirs in series and in parallel. M reservoirs in series are decomposed to M sub-problems of two reservoirs - one corresponding to a reservoir in the original problem and one representing the remaining (M-1) reservoirs. Archibald et al. (1997) present a decomposition technique that is applicable to more complex reservoir configurations. The original problem is decomposed into three reservoirs, one from the original problem (the focus reservoir), one aggregate reservoir for all upstream reservoirs and one for all the downstream reservoirs. M SDP problems are solved by varying the focus reservoir.

Aggregation methods combine reservoirs in the system to varying degrees (e.g., Saad et al. 1984). Although this considerably reduces the computational difficulty of the problem, much of the detail of the original problem is lost, e.g., individual capacities and operating restrictions. Disaggregation and application of the solution to the individual reservoirs becomes a major task. Aggregation techniques therefore seem to warrant the criticism that "many computer models successfully solve the wrong problem".

Nonlinear Programming

In contrast to LP and DP relatively little is published on the use of nonlinear programming (NLP) techniques for reservoir system operation. In his review of system analysis, Yeh (1985) concluded that NLP had proved unpopular due to its demanding computational requirements, resulting in long solution times. However recent rapid advances in computer processing speed and the availability of commercial non-linear solvers have made NLP a more attractive technique to practitioners. Unlike SDP, NLP cannot easily handle stochastic inflows, although NLP does not require discretization of decision and state variables. NLP techniques applied to reservoir operation include the gradient projection method (Lee and Waziruddin 1970), the conjugate gradient method (Lee and Waziruddin 1970), Lagrangian procedures (Chu and Yeh 1978) and reduced gradient algorithm (Rosenthal 1981, Lall and Miller 1988, Lefkoff and Kendall 1996).

Quantifying Objectives

Economic Loss Function

Optimization models use mathematical programming techniques to prescribe reservoir operation; therefore all objectives must be quantified. Economic valuation requires that monetary values be assigned to storage and flow in all parts of the system. While this approach has proved successful for traditional water uses, such as hydropower, flood control, irrigation and municipal water supply (see for example USACE 1991a and 1991b), valuation of environmental objectives has proved controversial (Colby 1990) and perhaps philosophically incompatible with how society would like to see water resource systems managed (Shabman and Stephenson 2000). Environmental objectives are usually better imposed through system constraints. Water use values must be expressed as mathematical functions. As many optimization models are formulated in terms of cost minimization, values are often represented in their inverted form as penalty functions; the point of maximum value is translated to the point of minimum cost. LP and NFP models require that all penalty functions are convex and piecewise linear.

As a surrogate for explicit economic values, many case studies in the academic literature minimize the variance of flows (and storages) from a target value. Alternatively quadratic loss functions have been assumed to express economic loss as a function of flow. Both two- and one-sided loss functions have been used[8]. From numerous studies on single reservoir operation some general conclusions can be made about the nature of the optimal operating policy. Young (1967) and Bhaskar and Whitlach (1980) found that optimal releases were independent of target demand for a two-sided loss function, but for one-sided loss function, releases are a function of the

[8] Flow in excess of the target in a one-sided loss function has a zero loss.

target (Bhaskar and Whitlach 1980). For a one-sided loss function Bhaskar and Whitlach found the optimal release policy corresponds to the SLOP. However as target demands increase the optimal policy becomes more non-linear.

Some general consequences of using different loss functions can be derived from Hashimoto et al. (1982). If the loss function for not meeting target demand is expressed as a power function, Hashimoto et al. (1982) show that vulnerability is a minimum for an exponent of two. For larger exponents, excessive carryover storage to reduce shortage under extreme droughts results in more severe deficits over relatively short time horizons. Reliability decreases with increases in the exponent as the optimal policy increasingly favors frequent shortages over infrequent large shortages. Resilience follows reliability. Failure becomes increasingly probable albeit at a low level of shortage.

Risk Aversion

Operation models typically often use average performance to determine optimal policies, such as the average costs or benefits over the period-of-analysis. Expected value is the most common criteria for decision making under conditions of risk or uncertainty. It leads to the greatest average benefit over time and is well suited to situations where many similar decisions must be made and when the range of performance consequences is relatively small (Arrow and Lind 1970). However the use of expected value to select optimal policies inherently assumes that decision-makers are not risk averse. In practice risk-aversion may determine operating policies. Some of the most conservative reservoir operations are for local flood control purposes and for local water supply where decisions are not only economic but also political. In these situations reservoir operators may be more concerned with system failure during extreme hydrologic conditions rather than economic efficiency or average performance. A risk-averse objective may be to minimize the worst case performance (e.g. water shortage or flood damage). This risk-averse behavior is further accentuated by the need to meet minimum instream flows and maintain reservoir levels for environmental and recreational purposes. Understandably operators are wary of implementing optimal policies from stochastic or probabilistic models. Consequently, reservoir operating rules are often based on deterministic models using critical-period analysis.

Several authors have analyzed operations under risk-adverse management. Risk is expressed mathematically by a probability distribution of possible outcomes. For water supply these are normally expressed in terms of an exceedance plot. Identification of an optimal management policy requires the transformation of a risk curve into indicators of desirability (Bouchart and Goulter 1998). Burt and Stauber (1971) argue that variability as well as expected value should be included as decision parameters. An “optimal” system operation may be defined by its response to a range of hydrologic events rather than evaluated in terms of the expected value. Several authors comment on the use of mean and variance to model risk preferences (Bosch et al. 1987, Hertz and Thomas 1983, Fleisher 1990). Loaiciga and Marino (1986) developed a reservoir model to minimize the variance of revenues subject to a constraint on expected revenues. A trade-off curve of expected revenues versus variance of revenues was generated by varying the expected revenue constraint. Decision makers may be driven more by the probability of loss or failure than variance. Maximin criteria may be more suitable in situations where decision makers are risk averse or the consequences of the worst outcome is unacceptable. Other selection criteria include maximizing reliability or the performance over a specified range and expected utility.

Various authors have investigated the trade-off between return and risk using dynamic programming. Askew (1974) introduced a penalty function, w, into the recursive formulation that had non-zero values only in the case of failure. This decreased net benefits associated with release decisions that could give rise to a possible failure, resulting in a more conservative optimum release policy. The expected number of failures for a given value of w was subsequently calculated using a simulation model. The trade-off between risk and returns was investigated by plotting expected benefits as a percentage of the maximum possible benefits (w = 0) against the average number of failures over a given period. Sniedovich and Davis (1975) showed that the expected value of failure could be represented as an additional state variable in the system and the trade-off obtained directly by DP. Hashimoto et al. (1982) used DP to investigate the relationship between reliability, resilience and vulnerability[9]. Reliability-constrained DP is well documented for the case of a single reservoir. However most DP formulations become intractable when applied to multi-reservoir systems, with streamflow interdependency (Yeh 1985). Thus the use of reliability-constrained DP remains restricted to simple systems.

Risk aversion is more of a practical political problem for reservoir operators than a real economic phenomenon for regional performance. Reservoir release decisions almost always have "small" consequences relative to the magnitude of the local economy. Thus from a regional economic perspective water supply and even moderate flood control decisions should be made from the perspective of expected value. For example, hydropower operation is mostly driven by expected value, as alternate energy is usually available from the rest of the grid.

Conclusions

The ingenuity of researchers combined with increases in computer processing speed enable ever more complex reservoir systems to be analyzed using stochastic mathematical techniques. While the stochastic approach better represents the decision process facing operators, its validity rests on the ability to develop a representative stochastic hydrology. For many stream systems having sufficiently long flow records, statistical techniques can be applied with reasonable confidence. However for climates where hydrologic persistence of drought or flood phenomena is evident, the reliability of statistical techniques becomes questionable. Convincing non-technical decision-makers of the validity of these techniques may be an even harder task than developing the hydrology. Operating rules developed from a stochastic optimization model require

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[9] Reliability is the probability that a reservoir can meet the target demand. It can be regarded as 1-probability of failure. Resilience is the conditional probability of being in a period of no failure given there was a failure in the last period, vulnerability is the maximum deficit during the period of operation/analysis.

testing using simulation of not one but many possible hydrologies using a Monte-Carlo approach.

Practitioners have historically been adverse to any form of optimization (although this appears to be changing) and academics have preferred the complexity and theoretical appeal of explicitly stochastic formulations. However due to the difficulties outlined in this chapter, engineers are likely to prefer deterministic optimization models to their stochastic counterparts. There is therefore a need for a new approach that can benefit from the simple deterministic approach of using the historic flow record, yet which better incorporates the uncertainties that operators face.

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4. SINGLE RESERVOIR OPERATION

Introduction

Despite development of new techniques, implicitly stochastic optimization (ISO) models solved using LP or NFP remain one of the most applicable to the analysis of complex systems. However the attribute of perfect foresight limits the immediate usefulness of such models and hinders the derivation of operating rules in subsequent simulation studies. This chapter presents a new method of incorporating risk and limited foresight into the ISO model. This is accomplished using sequential runs of the traditional ISO model with a rolling time horizon. The time horizon for each run is reduced to a fraction (1/n) of the period-of-analysis. The initial storage condition for a model run is set equal to the ending storage condition of the previous run. The series of n-linked consecutive runs form the optimal operating policy over the entire period-of-analysis. In this manner perfect foresight is limited to 1/n of the period-of-analysis. The consequence of reservoir release decisions on future model runs is represented by a value function on carryover storage at the end of each sequential run. This represents an implicit operating rule for carryover storage.

By using a hydrologic time series based on the historic record, the method avoids the difficulties of identifying and calibrating a suitable stochastic representation of inflows while directly representing the hydrologic variability observed historically. The method is demonstrated in this chapter by analyzing the operation of a single reservoir with dual purposes of flood control and water conservation. The objective function is formulated to minimize the economic cost of shortages associated with downstream agricultural deliveries. A generalized network flow algorithm with gains is used to find the optimal solution.

Several simulation models use optimization techniques to help prescribe system operation (Sigvaldason 1976; Bridgemen et al. 1988; Martin 1983, 1987; Chung et al. 1986; Kuczera and Diment 1988; Brendecke et al. 1989; Labadie 1997). Typically these models use the out-of-kilter network flow algorithm (Fulkerson 1961) to optimize operations over a single time step. Non-linear programming has been used in conjunction with simulation to determine optimal reservoir operating rules (Ford et al. 1981). The method described in this chapter extends these approaches. Optimization techniques are applied to prescribe optimal annual operations for a given carryover storage value function. Simulation type operating rules (although implemented through economic penalties) determine the trade-off between current deliveries and carryover storage. Non-linear search methods are used to define the optimal carryover value function.

New Modeling Approach

Economically driven optimization models minimize (maximize) system wide penalties (net benefits). Penalties may represent a mix of variable operating costs, shortage costs, flood damage and loss of hydropower benefits. The management of reservoirs operated for within-year storage can be modeled using a set of independent 12-month runs based on a representative set of reservoir inflows. However for reservoirs operated with carryover storage the annual sequence of inflows and operations becomes important. Reservoir operators make release decisions based on current storage, known demand (fixed by contractual agreements and requests) and forecasted inflows to the end of the water year. To better represent the decision process, the omniscience of the optimization model should be curtailed to the current water year. Single year's operations could be evaluated and optimized if a suitable penalty could be attached to the carryover storage condition. An optimization model run sequentially over the period-of-analysis using a 12-month rolling planning horizon will have some limited foresight. Although this may distort winter operations, its impact should be relatively minor. The individual 12-month model runs are linked via the beginning and ending storage conditions. The future value of water is represented by carryover storage values or penalties to prevent the model from over-pumping groundwater and draining surface reservoirs dry. The use of an economic objective rather than the more traditional objectives of maximizing yield, deliveries, power generation, etc., allows the model to trade current deliveries, e.g., to low-value agricultural crops, against future possible curtailment of deliveries, e.g., to high-value orchards during a drought. The success of the method relies on defining optimal carryover storage penalties.

Value of Carryover Storage

Figure 4.1 shows a hypothetical function for the value of carryover storage for a single reservoir. It is assumed that a minimum level of carryover storage is required either for maintenance of instream flows, cold water storage or other considerations that are not easily valued in dollar terms. In an optimization model this requirement can be set as a lower bound constraint. Above this lower bound it is assumed that the first derivative of the value of carryover storage is positive, i.e., an additional unit of carryover storage is always positively valued. It is also assumed that the second derivative is negative or that the function is concave, i.e., additional carryover storage has diminishing marginal value. If carryover storage is subsequently released to meet agricultural and urban demand, classical economics dictates that the marginal returns decrease with increasing supply.

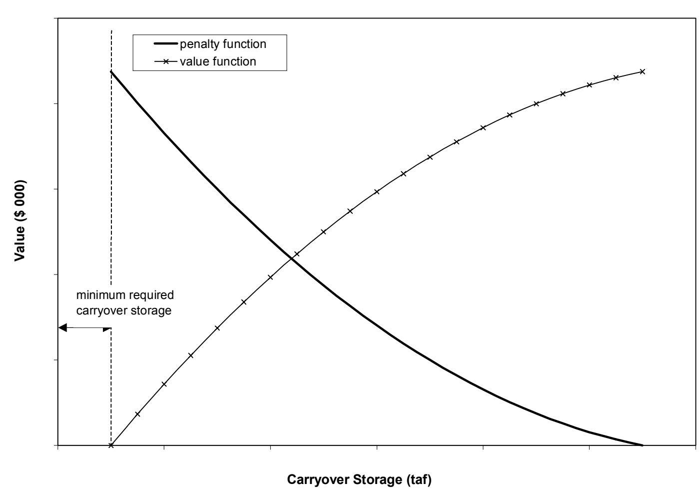

Figure 4.1 **Economic Value of Carryover Storage**

The value of carryover storage increases until storage is constrained by the physical capacity of the reservoir or flood limits to the top of the conservation pool. The value of carryover storage does not include the opportunity cost of any reduction in deliveries. To obtain a convex function for cost minimization, the value function is transformed into a penalty function that represents the cost of reducing carryover storage below some maximum value. It is important to note that this relationship holds only when water is a scarce resource and that there is a trade-off between current year water deliveries and carryover storage. Under wet conditions when the constraint on water availability is not binding, water is what economists call a "free-good" and excess water will remain in storage (due to the use small "persuasion" penalties). Depending on future inflows, this stored water may or may not have a value and may be spilled under wet conditions.

Many major water supply reservoirs combine water conservation with flood control objectives. This sets a practical limit to the volume of carryover storage. Figure 4.2 shows a typical flood control diagram. The flood season is divided into a rain-flood season and a snowmelt season. The reservoir must be drawn down at the beginning of the water year to create the required rain-flood space. This space is typically required for 2-3 months and then gradually decreases to zero. The snowmelt season overlaps with the end of the rain-flood season. The space required for control of snowmelt varies significantly according to the depth and water content of the snowpack, and is consequently termed conditional space. The objective of the reservoir operator is to refill the reservoir by the end of the snowmelt season without compromising flood control. Carryover storage in excess of K in Figure 4.2 will be spilled as the reservoir is drawn down for flood control. A practical upper limit to carryover storage, K_{cs}, is given by:

$$K_{cs} = K_p - V_{RFCP} - V_{\min} + \sum_{i=1}^{T} D_t + Min\left(\sum_{i=1}^{T} I_t\right) \qquad (1)$$

where K_p is the reservoir physical capacity, V_{RFCP} is the rain-flood control pool, V_{min} is the minimum operating storage, D_t is the target demand in month t, I_t is the reservoir inflow in month t, and T is the last month of the rain flood season (after which the rain-flood season is reduced). The last term in equation (1) represents the minimum total inflow from the start of the water year to the end of the rain flood season. For a deterministic model this can be set equal to the minimum inflow over the period-of-analysis.

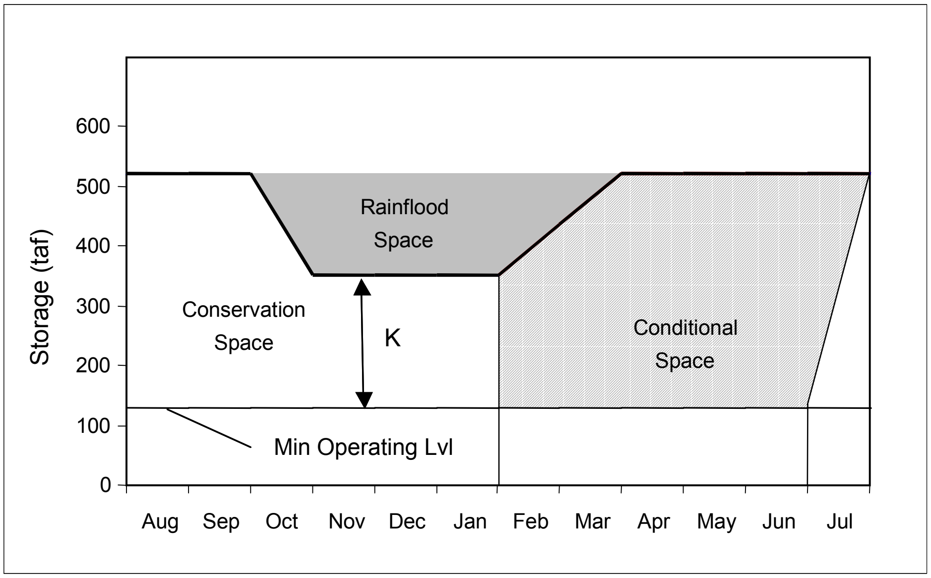

Figure 4.2 Flood Control Storage Diagram

To limit the number of parameters to be defined, it is assumed that the penalty on carryover storage can be represented as a quadratic:

$$P = aS^2 + bS + c \qquad (2)$$

where: P is the penalty ($); S is the EOP storage (af); and a, b, and c are constants ($/af^2, $/af, $). It is also assumed that the function will have a value of zero at the maximum carryover storage, K_{cs}. Although this last assumption may be incorrect, it does not matter, since it is the slope of the function, rather than the constant c, that affects the outcome of the optimization. The constant c is arbitrary, as far as the optimization model is concerned.

The first and second derivatives are:

$$\frac{\partial P}{\partial S} = P' = 2aS + b \qquad (3)$$

$$\frac{\partial^2 P}{\partial S^2} = P'' = 2a \qquad (4)$$

From the assumptions discussed above:

$$aK^2 + bK + c = 0 \qquad (5)$$ zero value at maximum storage

$$2aS + b \leq 0 \qquad (6)$$ negative marginal penalty values

$$2a > 0 \qquad (7)$$ diminishing returns to water

To give physical meaning to the unknown parameters, consider the values of the first derivative at S = 0 and at S = K_{cs}. The former represents the maximum willingness-to-pay for carryover storage, the latter represents the willingness-to-pay at the constraint imposed by flood control. Given the economics of agricultural production, these might represent a range from 0 \$/af to -500 \$/af. The constants a, b and c can be expressed in terms of these new parameters as:

$$b = P'\big|_{s=0} \tag{8}$$

$$a = \frac{P'\big|_{s=K} - P'\big|_{s=0}}{2K_{cs}} \tag{9}$$

$$c = -\frac{K_{cs}(P'\big|_{s=K} + P'\big|_{s=0})}{2} \tag{10}$$

Figure 4.3 shows the assumed feasible region for the two unknowns $P'\big|_{s=0}$ and $P'\big|_{s=K}$. For clarity, in the rest of the chapter $P'\big|_{s=0}$ will be denoted as P_{max} and $P'\big|_{s=K}$ as P_{min}.

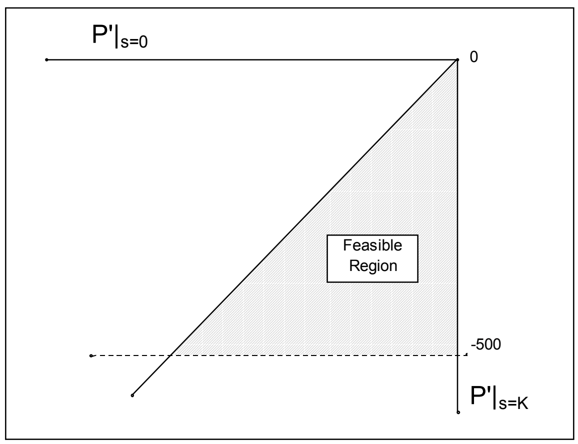

Figure 4.3 Feasible Region for Parameters of Carryover Storage Value Function

Implied Hedging Rule

For the optimal carryover storage, the marginal value of release equals the marginal value of storage. In the proposed model, penalties on deliveries and end-of-year storage are both quadratic in form. By equating the first derivatives of delivery and carryover penalty (or value) functions, it can be shown that the penalties are equivalent to a piece-wise linear hedging rule that specifies carryover storage in terms of the total water supply (less spills):

$$S_{cs} = \frac{b_d - b_s}{2a_s} + \frac{a_d}{a_s}D \tag{11}$$

where: S_{cs} is the carryover storage, D is the water released for delivery, b_d and a_d are the quadratic coefficients for the penalty on deliveries and b_s and c_s are the quadratic coefficients for the penalty on carryover storage. This result balances water between storage and deliveries. If total water availability (initial storage plus inflows) is represented by "A" so that $A = S_{cs} + D$, and A < maximum storage capacity plus maximum delivery so that water is scarce, then a hedging diagram can be established using this linear form for S_{cs} < capacity and D < maximum delivery. The "optimal" hedging curve when both deliveries and carryover have quadratic values is shown in Figure 4.4. In the spill range, water is not scarce and both carryover and delivery values are maximized to their constrained limits (just as in the spill portion of the SLOP rule). For water availability less than the non-scarce region of spills, Equation 11 applies as a linear hedging rule, beginning at the point of spill. Where this hedging line lies above the SLOP rule for higher values of A, but below spill, deliveries are constrained at their maximum and so remaining water is dedicated to storage. For lower values of A where the hedging line lies above the SLOP curve, delivery values have marginal values exceeding carryover storage, which is constrained to being non-negative; therefore carryover storage is zero for this range. Hedging does not always start at the spill point as indicated in Figure 4.4 but will depend on the relative marginal values of carryover storage and deliveries.

More complex hedging rules could be worked out for more complex polynomials of delivery and carryover storage values. This approach indicates that there is a clearly optimal form of hedging rule for different delivery value circumstances. For a single reservoir supplying a single demand, the use of a linear hedging rule for carryover storage would therefore seem justified. In this case the parameters of the rule would be included in the objective function and obtained directly using an LP model.

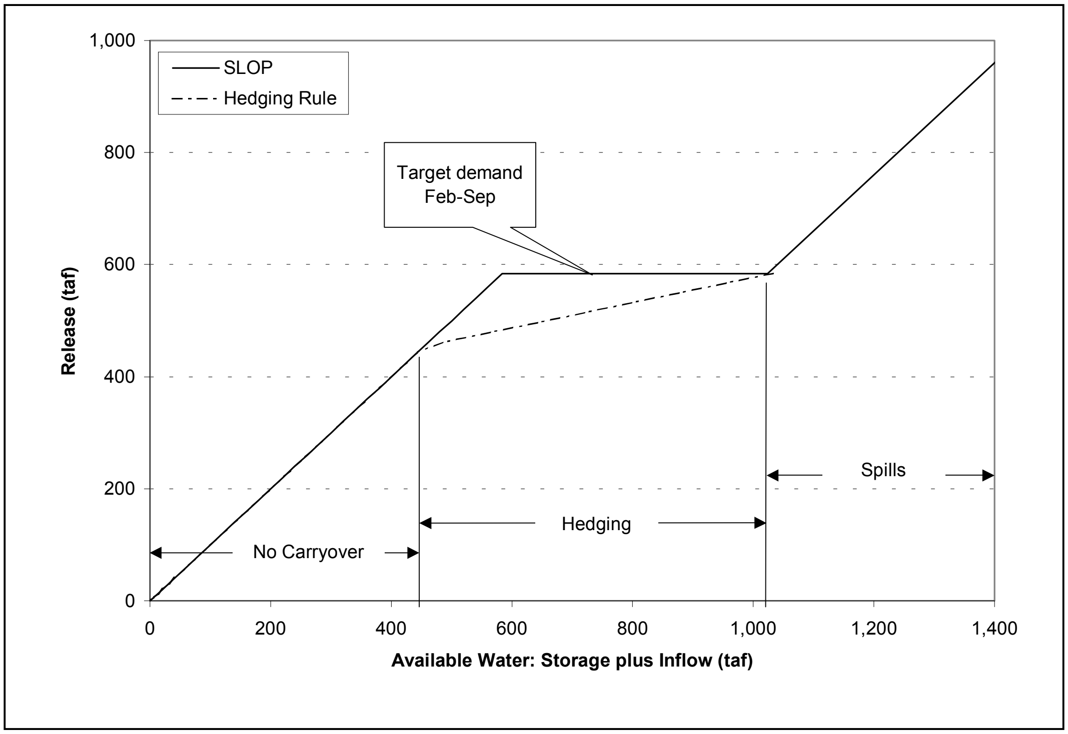

Figure 4.4 Hedging Rule for Carryover Storage

However for complex multi-reservoir systems supplying competing demands, carryover storage as a function of supply is probably highly non-linear and may vary between reservoirs. Specifying a suitable rule would require solving for the parameters of a piecewise rule. The difficulty of specifying complex decision rules that account for the many different state variables of a complex system is evidenced by single-period optimization methods embedded in simulation models.

Search Methods

An efficient search method will minimize the number of function evaluations required to locate the optimum solution, since this is by far the most time-consuming part of any method. Two parameters are needed to define a quadratic carryover storage penalty for a single reservoir of known fixed capacity. These parameters may be estimated using various non-linear search methods. The performance criteria for any pair of parameter values and the derived carryover storage penalty function is the sum of costs from the series of consecutive annual runs over the period-of-analysis. This excludes the penalties incurred for carryover storage, except for the last year of the period-of-analysis. Carryover penalties on storage provide the link from one year to the next and reflect operators (imperfect) knowledge of the probability of future inflows. However the carryover penalty for the last year of the model sequence should be included as it represents the future value of water beyond the period-of-analysis. This last carryover value function becomes less influential as the period-of-analysis increases. The two-parameter search can be expressed as a new non-linear optimization problem:

$$\text{Min } Z = \sum_{t=1}^{T}\sum_{m=1}^{12}\sum_{i=1}^{n} p_{mi} q_{tmi} + \sum_{j=1}^{R} p_{12j} s_{T12j} \qquad (12)$$

where: Z is the objective function; p_{mi} is the penalty on arc i in month m; q_{tmi} is the flow through arc i in month m in year t; n is the number of arcs; T is the number of years/sequential model runs; p_{12j} is the penalty on end-of-period storage for reservoir j in month 12; S_{T12j} is the end-of-period storage in reservoir j in year T in month 12; and R is the number of reservoirs. The first term is a non-linear function of P_{min} and P_{max} that is evaluated using T consecutive runs of the original optimization problem.

Search methods for defining P_{min} and P_{max} should be zero-order (function value search) applicable to constrained optimization where the solution may lie within (rather than on the boundary of) the feasible region. Calculation of first-order derivatives (gradient methods) is computationally burdensome, requiring evaluation of the function at two points separated by a small distance, for each input variable. Solution by linear programming requires linearization of the objective function. The functional surface will therefore be discontinuous, rather than smooth, with possible zero first-order derivatives when evaluated over small distances.

The application of non-linear search techniques to reservoir management is not new. Ford et al. (1981) used the Box-Complex search algorithm (Box 1965) in conjunction with simulation to determine storage zones for multi-objective reservoir operations. Simonovic and Marino (1980) applied a two-dimensional Fibbonaci search to examine the trade-off between risk (flood risk and drought risk) and benefits and so determine optimal reservoir operation. Nalbantis and Koutsagionnis (1997) used the uniform grid method to define optimal parameter values for a LDR for a multi-reservoir system.

Grid Search

The uniform grid method of parameter optimization is described in many standard texts (e.g. Loucks et al. 1981, pp65-68). The method involves creating a grid over the feasible region and evaluating the objective function at each grid point to find the point corresponding to the lowest function value. The method can be adapted so that the grid is successively reduced in the vicinity of the minimum. In successive iterations finer grids are nested within a selected area of the coarse grid. Function evaluation continues until the grid spacing reaches a specified convergence criterion. A grid search has the advantages that it is easy to implement, the response surface is mapped-out over the entire feasible region and a global minimum is obtained (albeit within the tolerance of the grid spacing). However it is inefficient in terms of the number of function evaluations required. It is therefore recommended that a coarse grid search be used to define a good starting point for more efficient methods.

Nelder-Mead Simplex Method[10]

The Nelder-Mead simplex method is applicable to minimization of mathematical functions of several variables. The method was first suggested by Spendley et al. (1962) and later developed by Nelder and Mead (1965). It is described in more detail in Appendix A. A simplex is a geometric figure formed by a set of n+1 points in n-dimensional space (Rao 1996, p368). The coordinates of each vertex define possible sets of input variables. The approach of the simplex method is to evaluate the function at the n+1 vertices of the simplex and gradually move the simplex towards the optimal solution through an iterative process. At each iteration, the value of the function at the vertices defines the direction of movement with the replacement of one or more of the original vertices by new points that have lower function values. The simplex adapts itself to the functional surface so that in three dimensions the simplex elongates down a long inclined planes, changes direction when it encounters a valley at an angle and contracts in the neighborhood of a minimum (see Figure 4.13). In comparative tests, Onwubiko (2000, p144) found the simplex method to be faster and more accurate than other multi-variable, zero-order search algorithms such as Hooke and Jeeves (1961) and Powell (1964).

The Nelder-Mead simplex method was developed for unconstrained minimization. Various techniques are possible to adapt the method to constrained minimization. Input variables may be transformed so that they are always located within the feasible region. Alternatively the function may be modified so that it will have a large positive value for all vertices located outside of the feasible region. For the current problem, the feasible region is constrained so that P_{max} and P_{min} are both negative and $|P_{max}| > |P_{min}|$. The method described by Nelder and Mead (1964) has been modified by the author so that if the expansion or reflection points lie outside the feasible region the reflection and expansion coefficients are decreased so that the new expansion or reflection point lies on the boundary. Care must be taken to choose an initial simplex that lies entirely within the feasible region. Functional evaluation is time consuming. The advantage of the simplex method is that it uses the least amount of information at each stage to define the next point in the search. During tests of the search method it was found that P_{min} often lay on the boundary of the feasible region. The simplex search method was modified to successfully cope with this eventuality. When the two vertices with the lowest function value lie on the boundary, a one-dimensional search is initiated. The simplex is expanded along the boundary until the minimum value is bounded. The Golden Section Search method (Rao 1996, p296) is subsequently used to locate the exact minima.

Global Optimum

Search techniques can be efficient sampling methods to identify the optimal value of system variables. However the Nelder-Mead Simplex method, outlined above, offers no guarantee that a global optimum has been identified unless the response surface is convex. It is recommended that a coarse grid search is used to check that a global minimum has been located.

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[10] This method should not be confused with the simplex method of linear programming.

Program Run Times

Despite the rapid evolution of computer processing speed, run times remain an obstacle to the analysis of very large and complex water resource systems. Typically network flow programming (NFP) codes undertake four main tasks: (a) to read the input file and data and generate the solver matrix; (b) to find an initial solution; (c) iterate to find an optimal solution; (d) and to write the output to file and store results. For simple systems involving one or a few reservoirs, the read and write times are a significant part of the total program run time. For larger systems they become less important. Run times for linear programming problems solved by the simplex algorithm are proportional to the cube of the number of functional constraints (Hillier and Lieberman 2001, p161) but are relatively insensitive to the number of variables. Both the number of variables and the number of functional constraints are proportional to the number of time periods. Figure 4.5 shows the program run times as a function of the number of time steps in the period-of-analysis. The problem is for a five surface reservoir, one groundwater reservoir system. Run times for this problem are approximately quadratic. In contrast for very simple single reservoir problems it was observed that run times increase at a linear rate. For complex systems the "limited foresight" model exploits this fairly rapid increase in run times. Although an iterative search is required, total run times for complex systems may be similar to a single perfect foresight run. As the complexity and length of the period-of-analysis increases, the limited foresight model may even offer a reduction in run times.

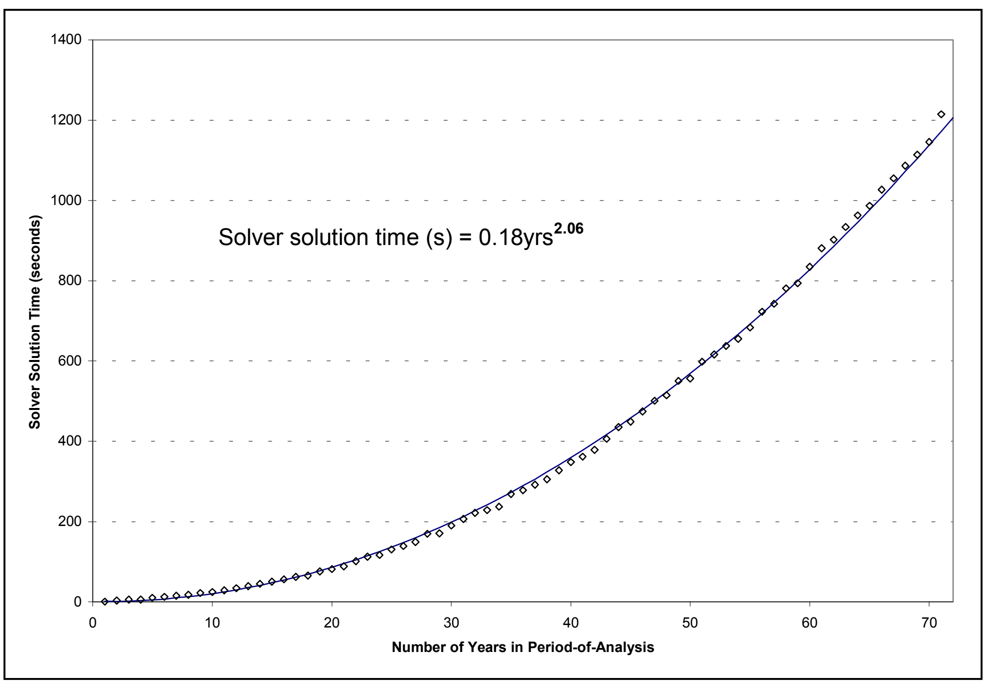

Figure 4.5 HEC-PRM Run Times

Case Studies

Description

It is suggested that due to perfect foresight, reservoir operation prescribed by traditional ISO models is significantly distorted. This affects the economic valuation of facilities and the subsequent determination of reservoir operating rules. An alternative limited foresight model has been described. To demonstrate the advantages of this new model and the potential drawbacks of the traditional perfect foresight model, a series of four case studies is presented. Each concerns the operation of a single instream reservoir with the dual purposes of flood control and water supply. Releases are made to satisfy a single downstream agricultural demand. For each reservoir three alternate operations (or model runs) are considered: (a) perfect foresight; (b) limited foresight; and (c) myopic operation. Perfect foresight corresponds to a single deterministic run for the period-of-analysis. Limited foresight corresponds to a series of sequential twelve-month runs over the period-of-analysis using carryover value functions to ensure adequate carryover storage. Finally myopic operation is as for limited foresight but with a zero carryover value (penalty) on storage. This corresponds to the standard linear operating policy (SLOP). Under myopic operation, the reservoir is always drawndown in times of shortage to the minimum operating level.

The four reservoirs are located in California's Central Valley: Lake Berryesssa on Putah Creek; New Don Pedro Reservoir on the Tuolumne River; Lake McClure on the Merced River; and Pine Flat Reservoir on the Kings River. These reservoirs represent a range of storage to mean inflow ratios. The reservoirs were selected as their operation is essentially independent of other storage facilities, they are predominantly used for irrigation supply and inflow data is readily available. New Don Pedro Reservoir, Lake McClure and Pine Flat Reservoir are all located in the western foothills of the Sierra Nevada Mountains. Their watersheds lie at high elevation so that the reservoir inflows are driven by snowmelt. Lake Berryessa is located on the eastern side of the Vaca mountains that form part of the California Coastal Range. Its watershed is at relatively low elevation so that reservoir inflow is predominantly rainfed.

(a) System Models

The purpose of the case studies is to provide a framework for the presentation of ideas rather than a realistic operation of each stream-reservoir system. The network representation of each system is shown in Figure 4.6. Reservoir evaporation and other system losses are ignored. The equation of state is:

$$S_{t+1} = S_t + I_t - R_t - Q_t \qquad (12)$$

where S_t is the reservoir storage (state variable) at the beginning of the time step t, I_t is the reservoir inflow (control variable) during time step t, R_t is the reservoir release (decision variable) to meet demand, and Q_t is the reservoir spill.

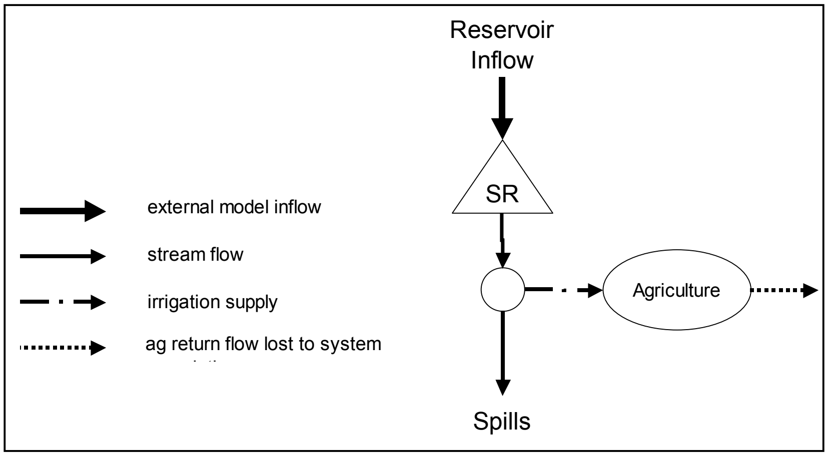

Figure 4.6 System Model

All models are run for a monthly time step using the historic hydrology modified to reflect 2020 land-use conditions. For Lake Berryessa and Pine Flat reservoir the period-of-analysis is water years 1922-1993; for New Don Pedro reservoir and Lake McClure the period-of-analysis is water years 1922-1994.

(b) Reservoir Inflows

Figure 4.7 shows the annual historic inflow to the four reservoirs for water years 1922-1993. Inflow statistics are given in Table 4.1, typical to California, the inflows show a high degree of variability.

Table 4.1 Reservoir Inflow Characteristics

Reservoir	River	Mean Inflow (taf/yr)	Standard Deviation (taf/yr)	Minimum (taf/yr)	Maximum (taf/yr)
Lake Berryessa	Putah Creek	372	275	28	1,228
New Don Pedro Res.	Tuolumne	1,518	886	214	4,380
Lake McClure	Merced	914	529	130	2,768
Pine Flat Res.	Kings	1,594	884	390	4,293

Figure 4.8 shows the average monthly cumulative inflow to the four reservoirs. Where inflows are driven by snowmelt, approximately 65% of the inflow occurs during the months of March, April and May. For Lake Berryessa inflows are derived from rainfall; 85% of the inflow occurs before March.

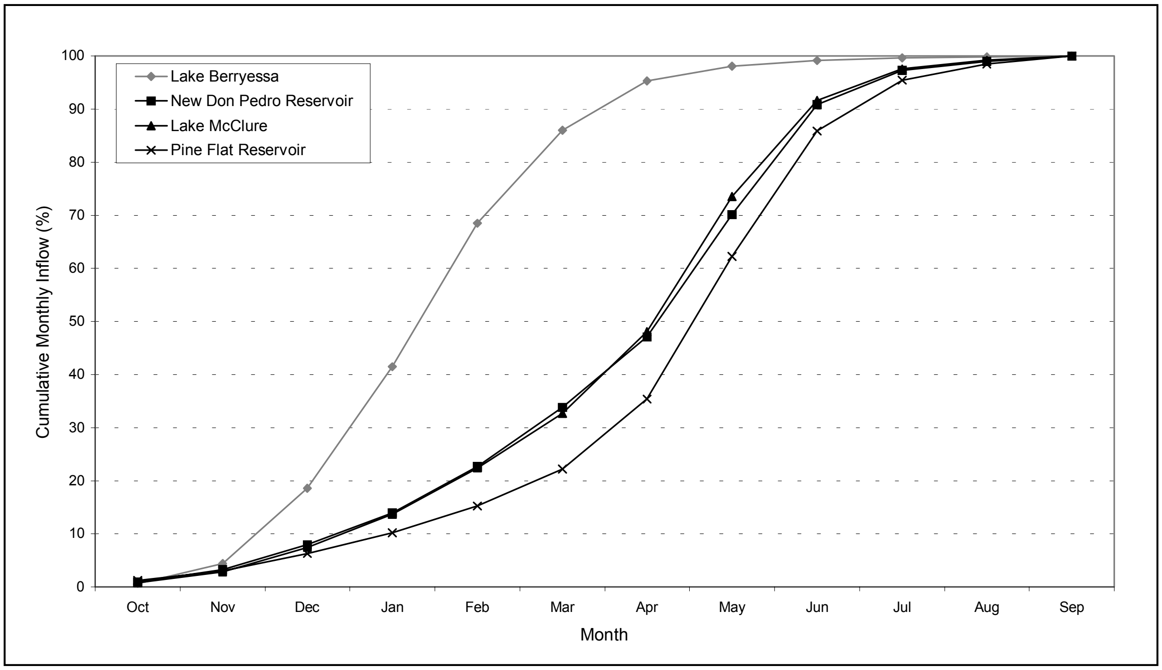

Figure 4.8 Average Monthly Distribution of Annual Reservoir Inflow

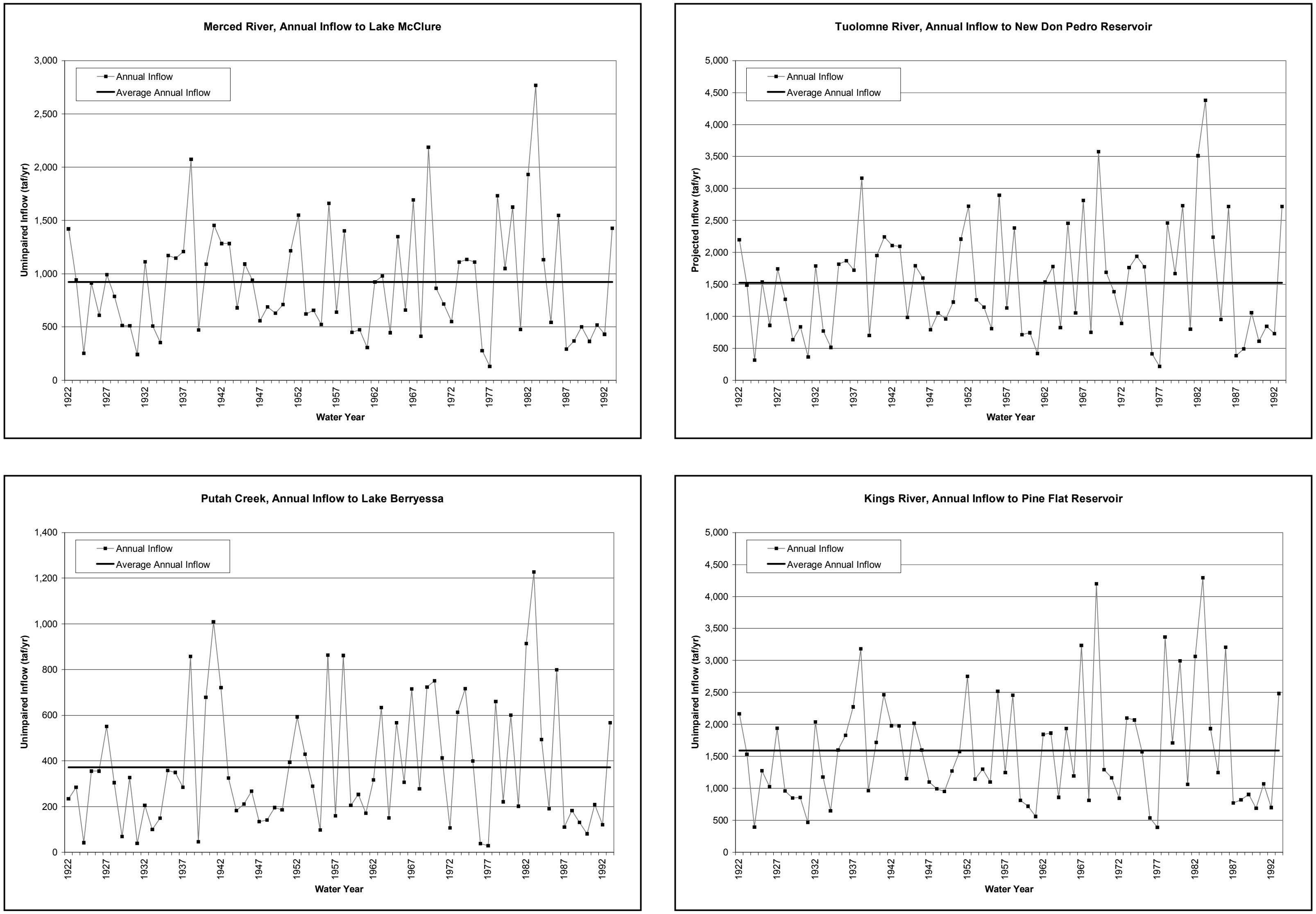

Figure 4.7 Annual Reservoir Inflow, Water Years 1922-1993

(c) Loss Function

A piecewise-linear approximation of a one-sided quadratic loss function is used to represent the cost of not meeting the agricultural target demand. Monthly quadratic functions were calculated using SWAP – an agricultural production model developed at the University of California at Davis (Howitt et al. 1999, Appendix A). Assuming farmers are rational and risk neutral, with a single objective of maximizing net revenues, SWAP uses quadratic programming to adjust *annual* resource allocation of land, water and capital to different crops. Constraints on the allocation of water across months ensure that the monthly crop water requirements are respected. The marginal value of water is imputed from the Lagrange multipliers for different levels of annual water availability using comparative statics. Monthly values are derived so that the marginal value of water is equal across all months. At the target demand the marginal value of water is zero. Monthly quadratic penalties are constructed by integrating the monthly values. To provide sufficient sensitivity to small changes in delivery, each monthly penalty function is approximated by 50 linear segments. For Lake Berryessa a significant fraction of releases are for urban water supply. To allow comparison with the other three case studies, demand is treated as being purely agricultural i.e., the agricultural demand is scaled to equal the total demand. It is assumed that levels of shortage are not sufficiently severe to reduce urban deliveries.

(d) Persuasion Penalties

Persuasion penalties are small unit penalties that are used to ascribe certain objectives or behavior to the model where it would otherwise be indifferent. To reduce the number of degrees of freedom, a persuasion penalty is attached to the agricultural return flow and stream outflow links. The persuasion penalty, though small compared to the cost of pumping and cost of shortage, tends to force a unique optimum solution to the problem. Where the model would previously be indifferent, water surplus to demand will be held in storage rather than spilled. The use of persuasion penalties thus results in a more realistic water supply reservoir operation.

(e) Supply Reliability

Parameters affecting supply reliability are given in Table 4.2. Vogel et al. (1999) suggests that over-year storage reservoirs are characterized by a high coefficient of variation of annual inflows ($C_v > 1$), and a low standardized net inflow ($m < C_v$)[11]. The supply reliability reported in Table 4.2 is the percentage of years that full demand is met under the SLOP.

Table 4.2 Reservoir Characteristics: Supply and Demand

Reservoir	Max Conservation Storage (taf)	Mean Inflow (taf/yr)	Inflow/Max Conservation Storage	Demand (taf)	Demand/ Mean Annual Inflow	Supply Reliability (%)
Lake Berryessa	1,592	372	4.28	340	0.91	86[1]
New Don Pedro Res.	1,721	1,518	1.13	1,015	0.67	86

[11] The standardized net inflow or m index was introduced by Hazen (1914) and is defined as the mean annual inflow less the average yield divided by the standard deviation of the annual inflow.

Lake McClure	851	914	0.93	605	0.66	84
Pine Flat Res.	956	1,594	0.60	1,545	0.97	35

Notes
1 Lake Berryessa has a very high supply reliability so that reservoir performance is optimal under the standard linear operating policy. For this case study demand has been arbitrarily increased by 100 taf/yr. The total demand given is the sum of the 100 taf/yr plus an estimated 16 taf/yr riparian use, 12 taf/yr stream losses, 151 taf/yr ag demand as part of the Solano Irrigation Project and 41 taf/yr urban demand as part of SIP. In addition minimum instream flow requirements d/s of urban and agricultural diversions is 20 taf/yr. Source SCWA (1996)
2 Source: DWR, File dwrsim 2020d09b-calfed-514 and USBR (1997), Files cvpeis\disc2\sanjasm\naa\input\fwreq.n22,pdem.nc1,npdem.n22,res.nd1
3 Source: DWR, File dwrsim 2020d09b-calfed-514 and USBR (1997), Files cvpeis\disc2\sanjasm\naa\input\fwreq.n22,pdem.nc1,npdem.n22,res.nd1
4 Source: California Data Exchange Center, Kings River at Pine Flat, full natural flow, and USBR (1997), Files cvpeis\disc2\cvgsm\naa\input\cnjswdv3.nea, cnjdvsp2.nda

<u>(f) Carryover Storage Capacity</u>

The maximum carryover storage capacity is given by equation (1). Its five determinants are given in Table 4.3. New Don Pedro Reservoir has the greatest storage capacity; Pine Flat reservoir the least.

Table 4.3 Carryover Storage Capacity

Reservoir	End of Rain-flood Season	Min Inflow[1] (taf)	Max Demand[1] (taf)	Max Reservoir Capacity (taf)	Min Operating Volume (taf)	Max Rainflood Control Space (taf)	Carryover Storage Capacity (taf)
Lake Berryessa	N/A[2]	N/A[2]	N/A[2]	1,602	10	N/A[2]	1,592
New Don Pedro	1st Mar	36	37	2,030	309	440	1,208
Lake McClure	1st Mar	10	22	1,024	173	348	476
Pine Flat	1st Feb	39	21	1,001	45	475	421

Notes: 1. From start of water year to end of the rain flood season
2. Lake Berryessa is not operated for flood control

Computation

Reservoir operation was evaluated using the USACE's Hydrologic Engineering Center Prescriptive Reservoir Model (HEC-PRM). HEC-PRM is a generalized network flow program with gains (USACE 1994). The model was originally developed to analyze multi-reservoir systems on the main-stem of the Missouri River (USACE 1991b, 1992a) and the Columbia River (USACE 1991a, 1993). It has been since been applied to the Carson-Truckee system in California (Israel and Lund 1999), the Alamo Reservoir in Arizona (USACE 1998a), lake-reservoir systems in South Florida (USACE 1998b), and the Panama Canal (USACE 1999). HEC-PRM analyzes multi-period reservoir operation as a minimum cost network flow problem. Both conveyance and storage are represented by arcs, either in space or time. Objectives are represented as penalties or costs associated with flows through arcs. HEC-PRM determines the spatial and temporal allocation of flow through the 3-dimensional network that minimizes the total system cost over the period-of-analysis.

All model runs and program execution are controlled using Microsoft's Visual Basic. Reservoir operation under perfect foresight requires execution of a single run of HEC-PRM. Myopic operation requires a single set of 72 or 73 sequential runs; after each run the input file time period is advanced one year and the initial storage condition set equal to the ending storage of the previous run. Under limited foresight many sets of 72-73 sequential runs are required to refine the optimal carryover storage penalty function. An initial grid search was carried-out for the two parameter values, P_{min} and P_{max} , to provide a suitable starting point for the Nelder-Mead simplex search and map-out the response surface. For all reservoirs the grid search suggests that the objective function is relatively flat in the vicinity of the optimal values of P_{min} and P_{max} , and they are difficult to precisely identify. The optimal value of P_{min} is near zero. Figures 4.9-4.12 show the response surface for the four case studies determined using a 20$/af spaced grid search. Figure 4.13 shows for Lake McClure the iterative steps of the subsequent simplex search to find a more precise optimal at (-9, -148) from an initial user defined starting point.

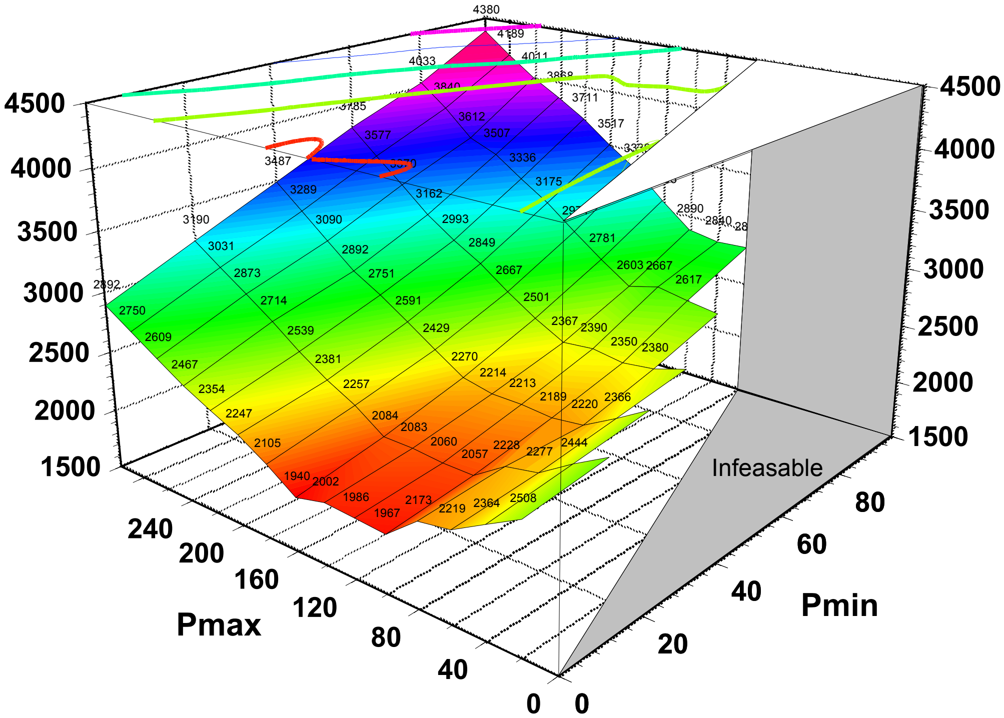

Figure 4.9 Lake McClure, Average Annual Shortage Cost ($000) as a Function of P_{min} and P_{max} ($/af)

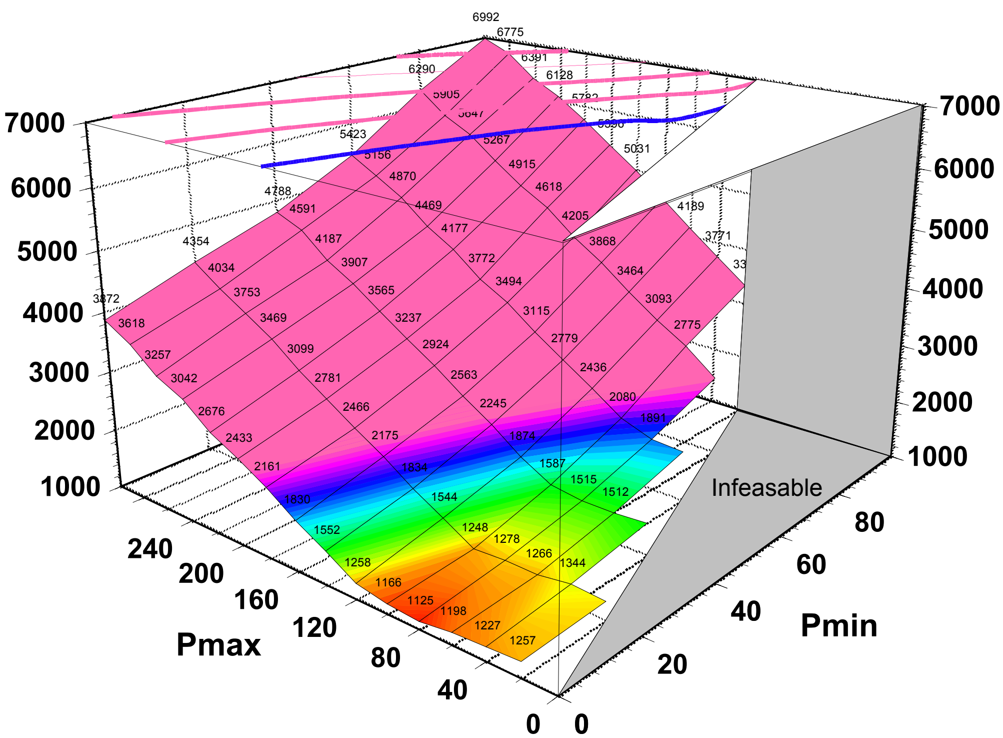

Figure 4.10 New Don Pedro Reservoir, Average Annual Cost ($000)as a Function of P_{min} and P_{max} ($/af)

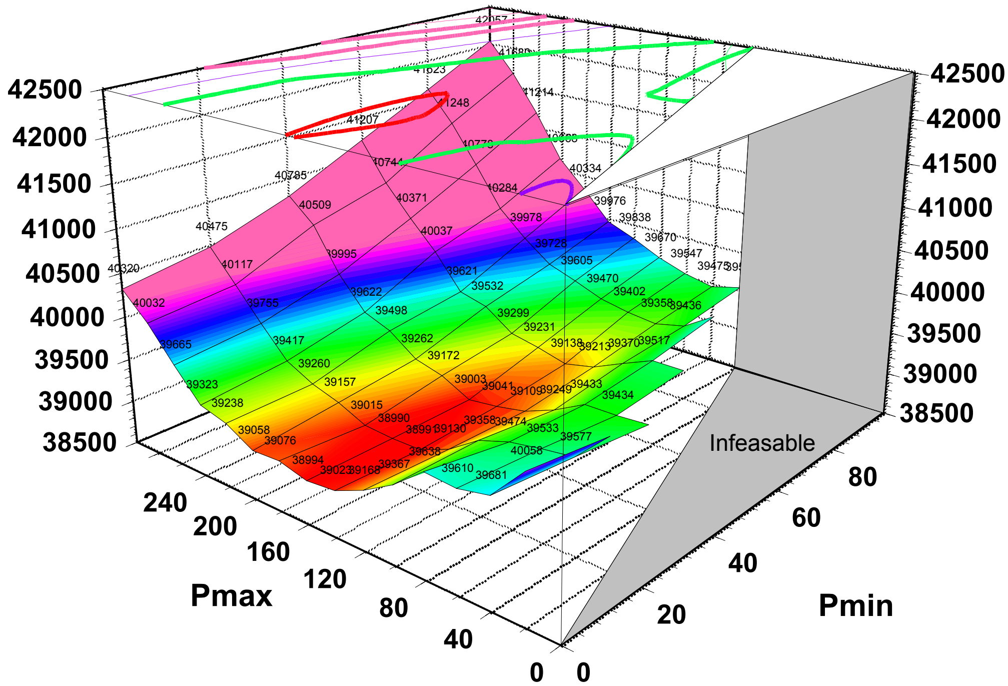

Figure 4.11. Pine Flat Reservoir, Average Annual Shortage Cost ($000) as a Function of P_{min} and P_{max} ($/af)

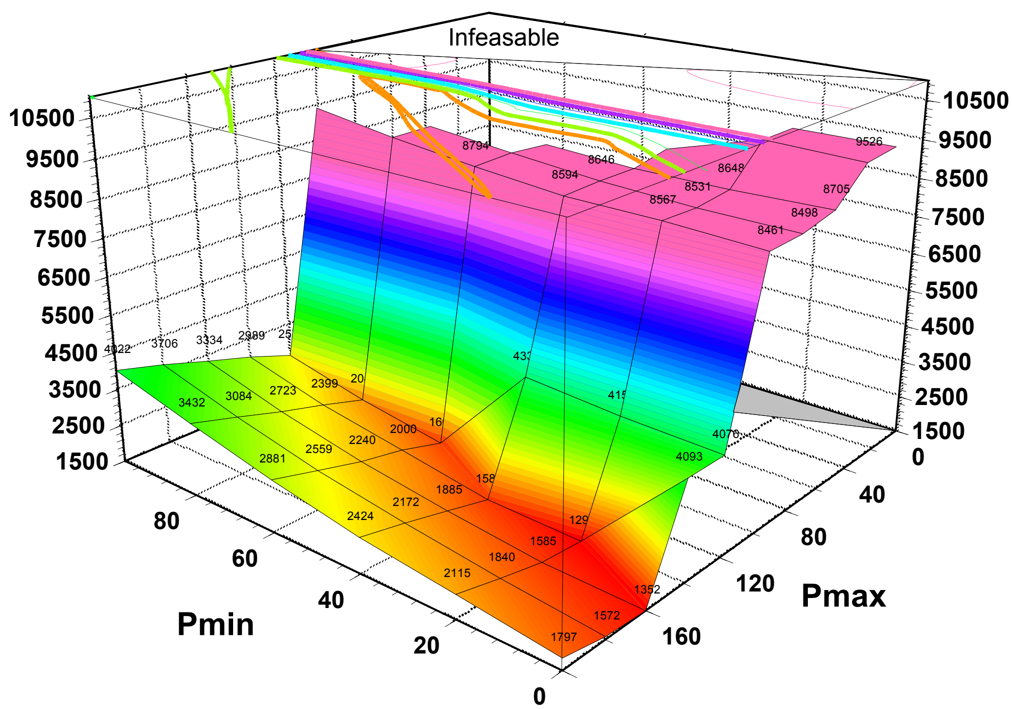

Figure 4.12 Lake Berryessa, Average Annual Shortage Cost ($000) as a Function of P_{min} and P_{max} ($/af)

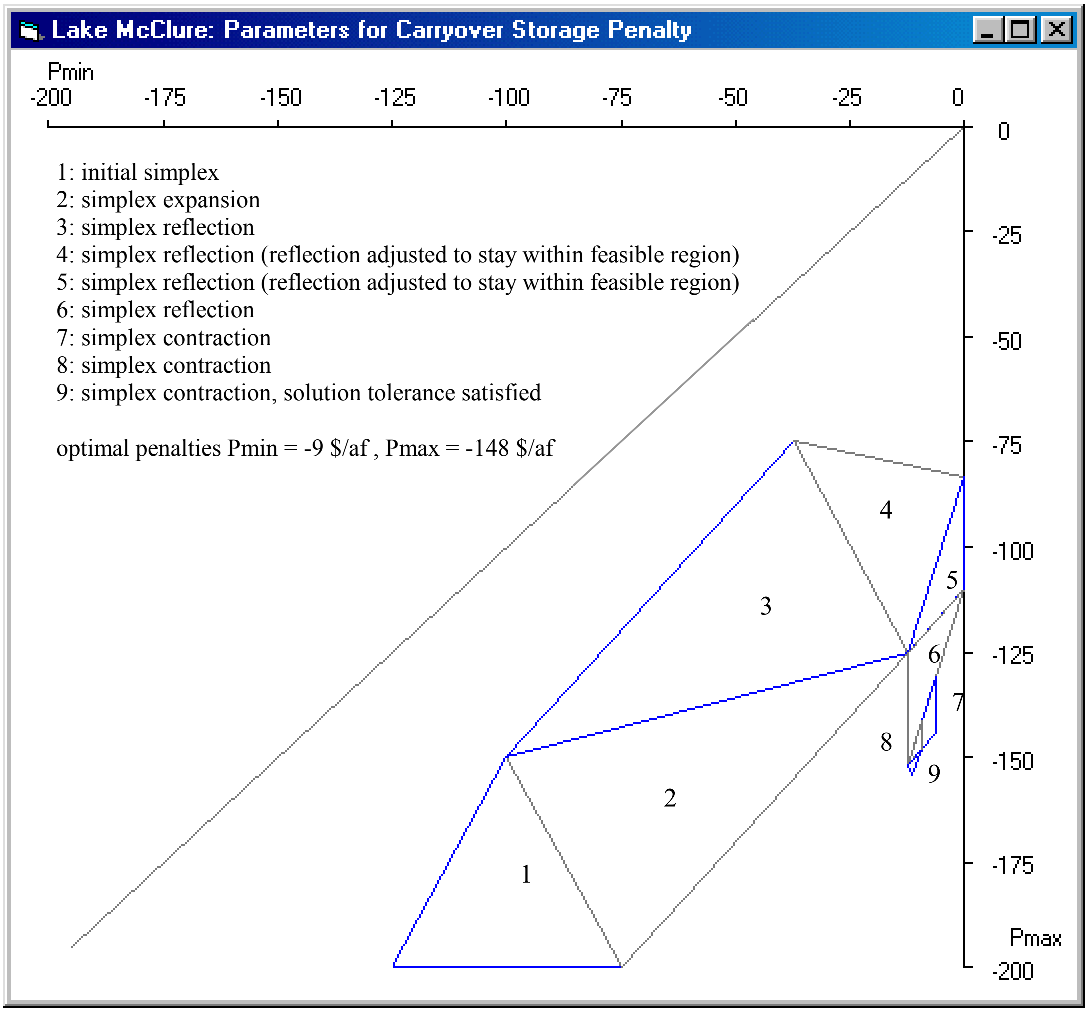

Figure 4.13 Simplex Reflection, Expansion and Contraction

Results

Summary results for the operation of each of the four reservoirs under the three different scenarios (perfect foresight, limited foresight, myopic operation) are given in Tables 4.4 to 4.7.

<u>(a) Shortages and Costs</u>

For Lake McClure and New Exchequer Reservoir the results have a similar pattern. Myopic operation corresponds to the SLOP. During shortages this policy results in the release of all water from storage; average annual shortages are therefore always minimized. Perfect foresight allows for optimal hedging; the total shortage over the period-of-analysis is identical to the myopic scenario. However, through the judicious use of carryover storage, extreme shortage events are avoided. Average annual shortage costs are 35% - 47% of the myopic operation. The SLOP performs particularly badly by often failing to provide sufficient carryover storage to meet demand in the months prior to the refill season, especially so prior to dry years when the start of the refill season is delayed. The performance of the SLOP could be improved by using a 12-month period running from December to the following November. Under limited foresight the model hedges deliveries as an insurance against forthcoming drought. These hedges are sometimes successful and sometimes not. Average annual shortages are 56% - 86% higher than for the other two scenarios. However shortage costs are 66% - 74% of myopic operation. The performance of the limited foresight model lies approximately mid-way between perfect foresight and myopic operation and suggests that the achievements of the perfect foresight model are unattainable in practice.

The results for Lake Berryessa are atypical. The reservoir has a low mean annual inflow to storage ratio of 0.23. Existing annual demands are well below the mean annual inflow resulting in a highly reliable reservoir with no shortages observed over the 72-year historic period. For this case study annual demands were increased artificially to 91% of inflow, making the system much more vulnerable to shortages. A mass diagram shows of annual inflows shows relatively long cycles of wet and dry periods; low inflows between 1922-1950, followed by high inflows between 1951-1986. Under myopic operation the initial dry period causes a gradual but sustained drawdown that finally results in extreme shortages between 1932-1950. Myopic operation therefore results in the highest level of shortages and shortage costs. The majority of these shortages can be avoided through a small amount of hedging. The results for Pine Flat Reservoir follow the pattern of Lake McClure and New Don Pedro Reservoir, except that the additional benefits of limited and perfect foresight are relatively modest compared to the SLOP. The low storage to inflow ratio for this reservoir limits the possibilities to hedge as spills during the refill period are relatively frequent.

(b) Interpretation of Lagrange Multipliers and Marginal Values

Economically driven LP models provide economic information in terms of dual values (Lagrange multipliers) and reduced costs. These are respectively the value of a unit relaxation of a binding constraint and the cost of a unit change in the value of a non-basic decision variable. HEC-PRM differs from standard LP models in that it reports the marginal value (of additional water) rather than the reduced cost.

The Lagrange multipliers on the reservoir upper bound constraint and the marginal value of additional reservoir inflows are indicators of the value of capacity expansion, and the opportunity cost of upstream use or the value of upstream development to re-regulate streamflow. The average annual values of the monthly time series of the Lagrange multipliers on the upper bound reservoir storage constraint represents the annual expected value (EV) of an additional unit of storage capacity. This capacity could be achieved through either a relaxation of flood storage requirements or an increase in the physical capacity of the reservoir[12].

[12] Lagrange mutipliers on the upper bound constraint are very close in magnitude (opp in sign) to those on the lower bound.

Table 4.4 Model Results for Lake McClure

Time Horizon	Average Annual Shortage	Average Annual Cost of Shortage	Average Shadow Price on Reservoir Capacity	Average Marginal Value of Reservoir Inflow
	(taf/yr)	($ 000/yr)	($/af/yr)	($/af/month)
Perfect Foresight	18	1,232	6.0	18.0
Limited Foresight	27	1,944	4.9	-
Myopic	18	2,622	9.6	-

Table 4.5 Model Results for New Don Pedro Reservoir

Time Horizon	Average Annual Shortage	Average Annual Cost of Shortage	Average Shadow Price on Reservoir Capacity	Average Marginal Value of Reservoir Inflow
	(taf/yr)	($ 000/yr)	($/af/yr)	($/af/month)
Perfect Foresight	15	558	2.4	8.7
Limited Foresight	28	1,064	3.0	-
Myopic	15	1,595	4.9	-

Table 4.6 Model Results for Lake Berryessa

Time Horizon	Average Annual Shortage	Average Annual Cost of Shortage	Average Shadow Price on Reservoir Capacity	Average Marginal Value of Reservoir Inflow
	(taf/yr)	($ 000/yr)	($/af/yr)	($/af/month)
Perfect Foresight	9	429	1.4	19.7
Limited Foresight	31	1,290	-	-
Myopic	35	10,938	-	-

Table 4.7 Model Results for Pine Flat Reservoir

Time Horizon	Average Annual Shortage	Average Annual Cost of Shortage	Average Shadow Price on Reservoir Capacity	Average Marginal Value of Reservoir Inflow
	(taf/yr)	($ 000/yr)	($/af/yr)	($/af/month)
Perfect Foresight	242	33,718	40.9	102.9
Limited Foresight	256	39,426	-	-
Myopic	242	40,168	-	-

To check the dual values have been correctly interpreted, model runs for Lake McClure and New Don Pedro Reservoir were rerun with one additional unit capacity. Under perfect foresight the Lagrange multipliers correctly predicted the value of additional storage. However under limited foresight and myopic operation, the EV of the Lagrange multipliers over-estimated the value of additional storage. For myopic operation this is expected, as carryover storage is not valued. In wet years when full demand is met, increasing storage capacity to increase carryover storage will not be valued by the model, although it might subsequently result in reduced future penalties.

For limited foresight, although the carryover storage penalty function is 'optimal' in the sense that it results in the least total penalty over the period-of-analysis, it does not represent the true future value of water in storage given knowledge of the future hydrology. Values given in Tables 4.4 to 4.7 for limited foresight and myopic operation are calculated by comparing results from two model runs with a unit difference in storage capacity. The column has been labeled "shadow price" rather than Lagrange multiplier to emphasize this point.

Perhaps surprisingly, perfect foresight overestimates the value of additional storage for Lake McClure and understates it for New Don Pedro compared to the limited foresight scenario. Two opposing mechanisms are at play. Under limited foresight, shortage and shortage costs are greater so that additional storage has greater value. However under perfect foresight, additional storage is used more efficiently. The relative magnitude of the two effects depends on the degree of shortage and the curvature of the loss function. Consider a dry period of n years at the start of which the reservoir is full and which ends when the reservoir refills and spills. Under perfect foresight carryover storage is allocated (if possible) to equalize the storage between years, so that an additional unit of storage reduces the annual shortage by 1/n taf . Under limited foresight total deliveries during the dry period will be less than under perfect foresight due to hedging in the final year, which is subsequently spilled. Initially deliveries under limited foresight may exceed those under perfect foresight but in following years be less. An additional unit of storage will result in a reduction in annual shortage of less than 1/n. For the Lake McClure model, perfect foresight over-estimates the value of storage by 22% compared to limited foresight. Myopic operation over-estimates its value by 96%. For the New Don Pedro the perfect foresight model under-estimates the value of storage by 20% compared to limited foresight. Myopic operation results in a 63% over-estimate compared to limited foresight.

<u>(c) Carryover Storage for New Don Pedro Reservoir</u>

Deliveries and storage operations for New Don Pedro reservoir were compared for three sets of model runs corresponding to perfect foresight (single 73 year run), myopic (73 twelve-month runs with no penalty on carryover storage) and limited foresight (73 twelve-month runs with optimal penalty on carryover storage). The results are shown in Figures 4.14, and 4.15 and 4.16.

Under perfect foresight there are few periods of delivery deficiencies. During these periods, notably during the 1987-1992 drought, shortages are approximately equalized across the drought through optimal hedging. Only during, or immediately prior to drought is water assigned to carryover storage at the expense of not meeting current demand, i.e., only in 11 out of 73 years does the model hedge.

Under myopic operation there are similarly four periods of shortage but annual shortages show much greater variation within a particular drought period and peak shortages are more extreme. Oddly the figure suggests that hedging (i.e., carryover storage is above minimum in years of shortage) occurs in four years: 1932; 1962; 1978; and 1993. However inspection of the results shows that this is not "true" hedging. In these years deficiencies occur in October prior to winter inflows and that subsequently after the refill period there is excess water so that some water is held as carryover storage.

Deliveries under limited foresight are much more variable. Constant hedging results in numerous small shortages. The model now hedges in 34 out of 73 years. In 12 of these years some or all of this storage is lost as spills in the following refill season.

Figure 4.17 compares carryover storage for the three scenarios. Myopic operation always results in the least carryover storage. In most years limited foresight results in excessive carryover storage (i.e., some or all of this water is spilled). However prior to the 1976-1977 two-year drought and the 1987-1992 six-year drought, carryover storage is insufficient, i.e., less than what would be assigned under perfect foresight.

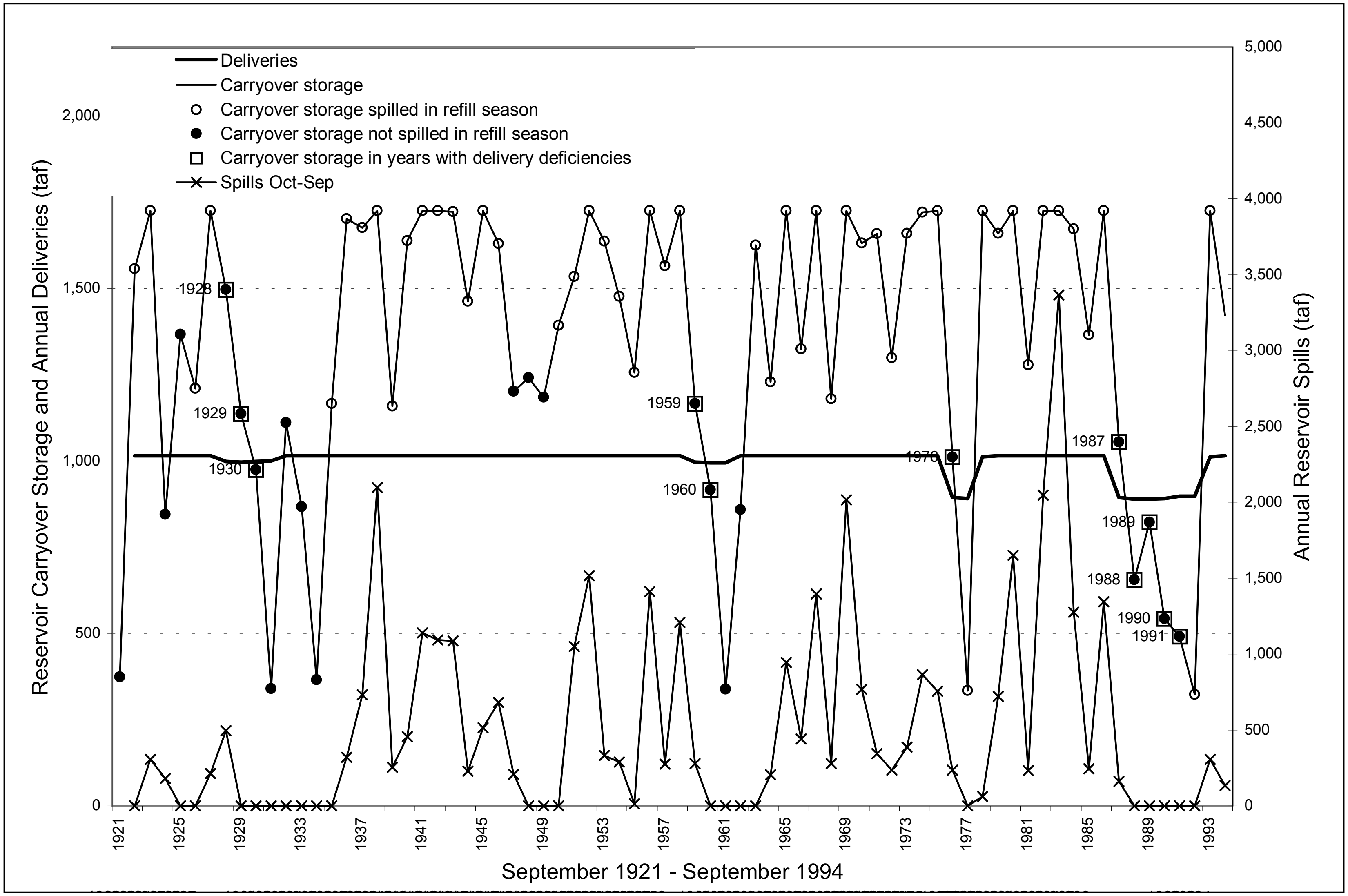

Figure 4.14 New Don Pedro Reservoir Operation under Perfect Foresight

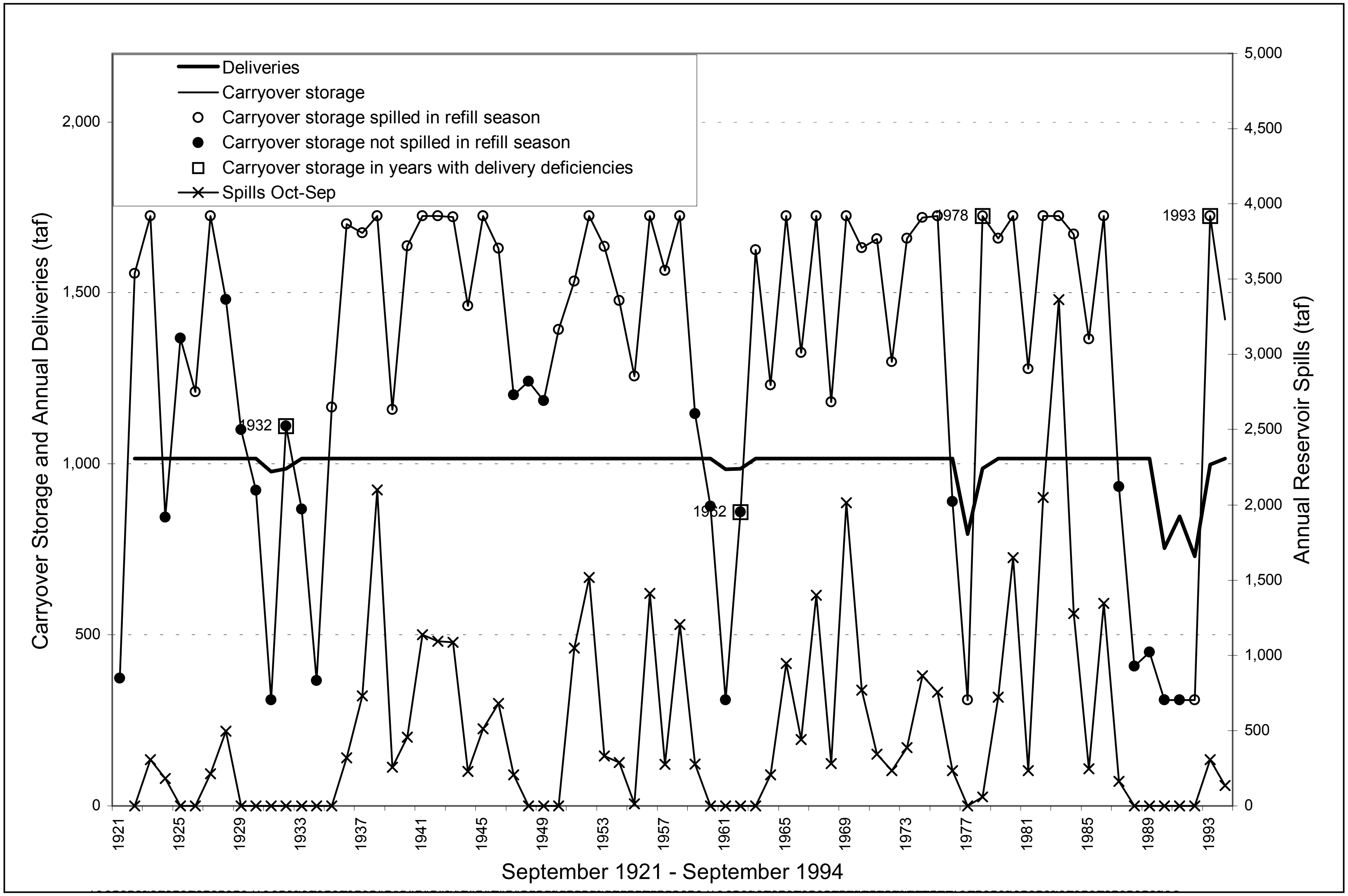

Figure 4.15 New Don Pedro Reservoir under Myopic Operation - Standard Linear Operating Rule

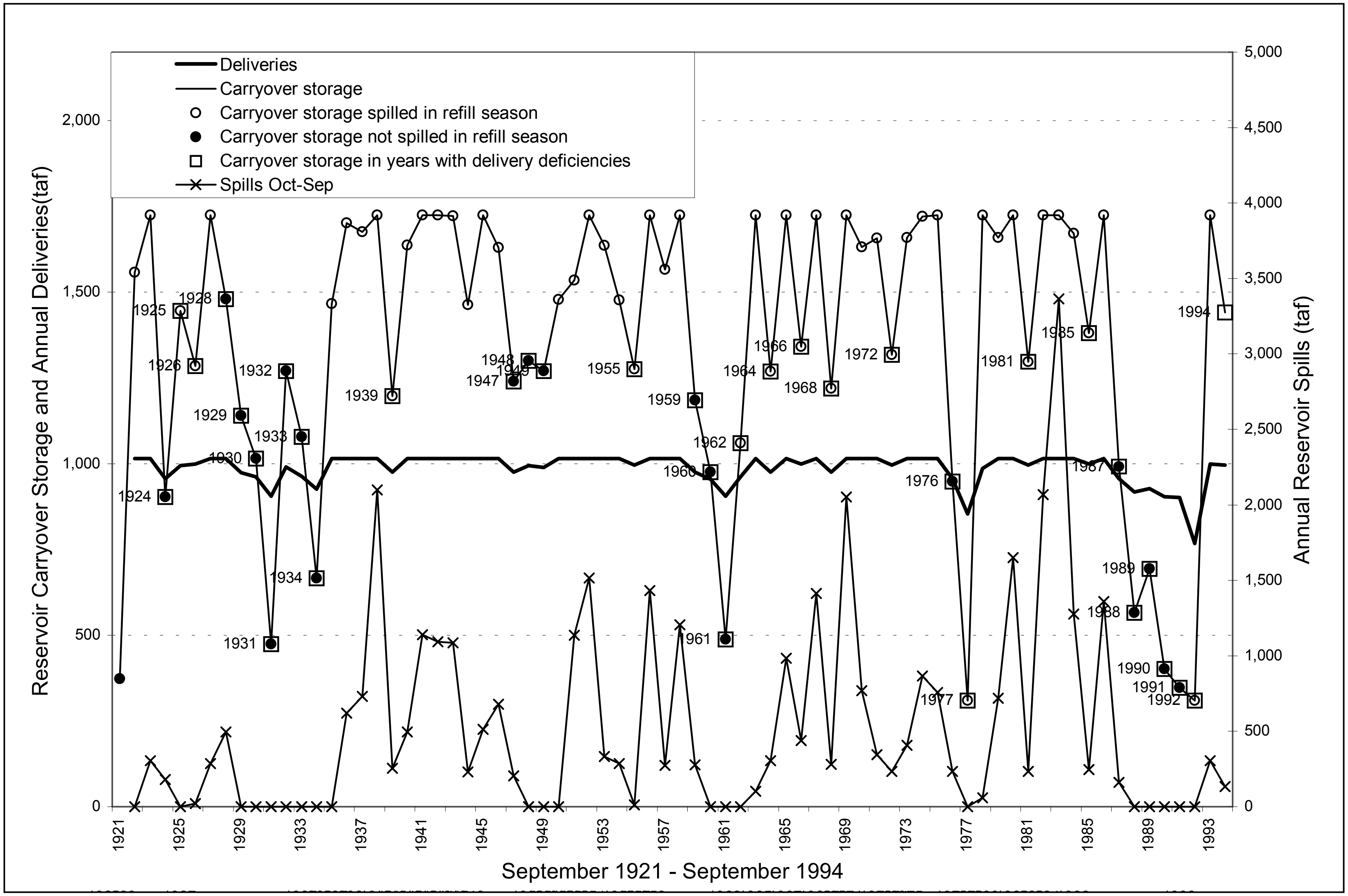

Figure 4.16 New Don Pedro Reservoir Operation under Limited Foresight

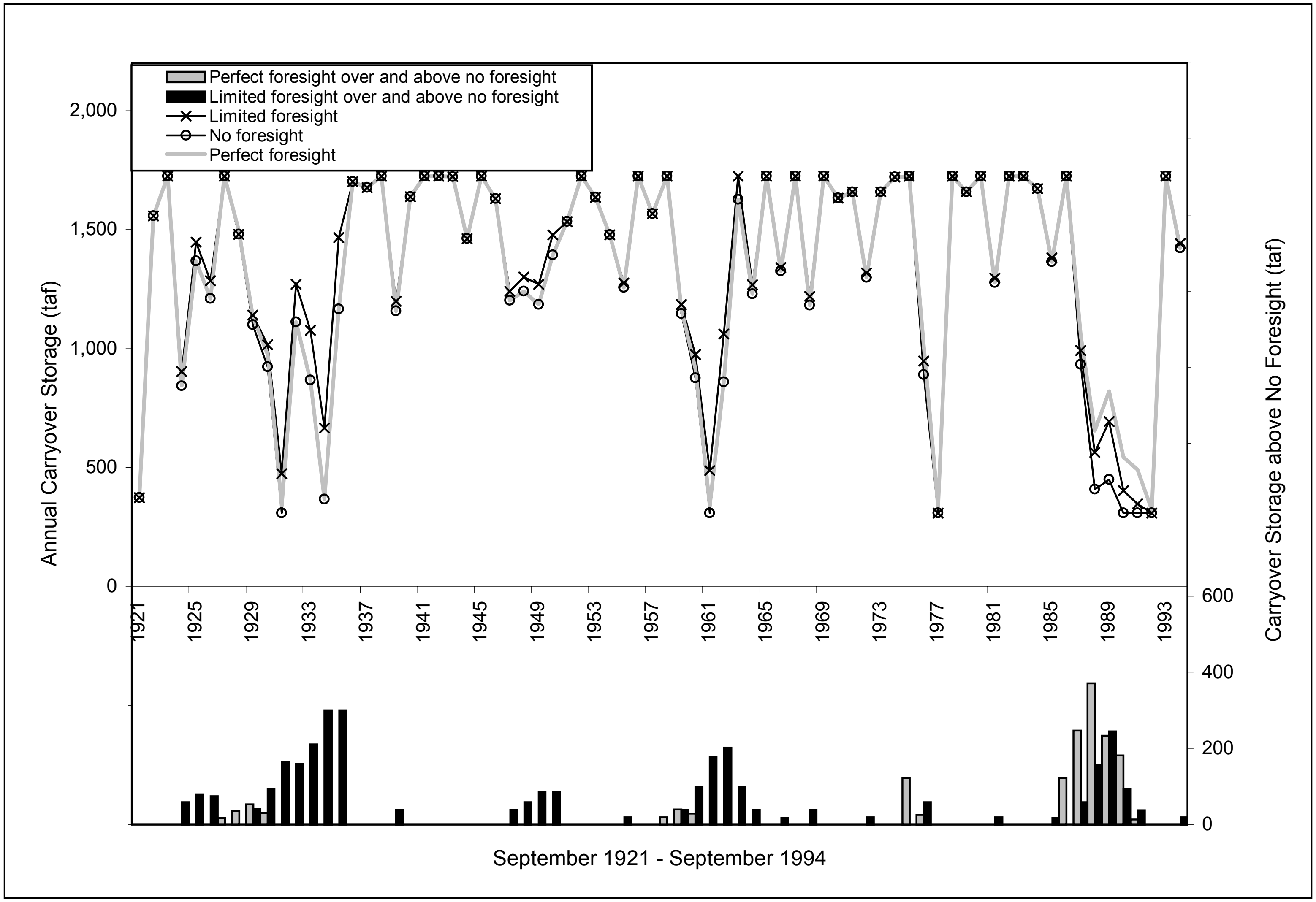

Figure 4.17 New Don Pedro Reservoir Carryover Storage for Different Levels of Information

It is worth noting that during a single year drought the SLOP is superior to the limited foresight operation as it drains the reservoir. Limited foresight performs better under multi-year droughts.

(d) Average versus Minimum Deliveries

Carryover storage provides some insurance against future low inflows that would cause severe shortages and shortage costs. However carryover storage decreases the ability of a reservoir to capture winter runoff during the flood season. This trade-off is illustrated using results from New Don Pedro Reservoir. Figures 4.18 and 4.19 show shortages and shortage costs as a function of the carryover storage penalty. P_{min} is held constant at zero while P_{max} is varied from zero to 300 $/af. In Figure 4.18 annual average shortages rise as carryover storage is increasingly valued leading to greater spills during the refill season. Correspondingly deliveries fall. However the maximum annual shortages show a minimum around $100/af. In Figure 4.19 the average annual cost also has a minimum at a slightly lower value of P_{max} of $80/af. The percentiles of annual cost show minimums for different values of carryover storage. The maximum annual cost has a minimum for a relatively highly valued carryover storage of $100/af. The 92% percentile shows a minimum at a lower value of 20$/af. This has some implications for risk-averse decision-makers. The effect of increasing the value of (and actual) carryover storage is to increase the average shortage but decrease the maximum and variance.

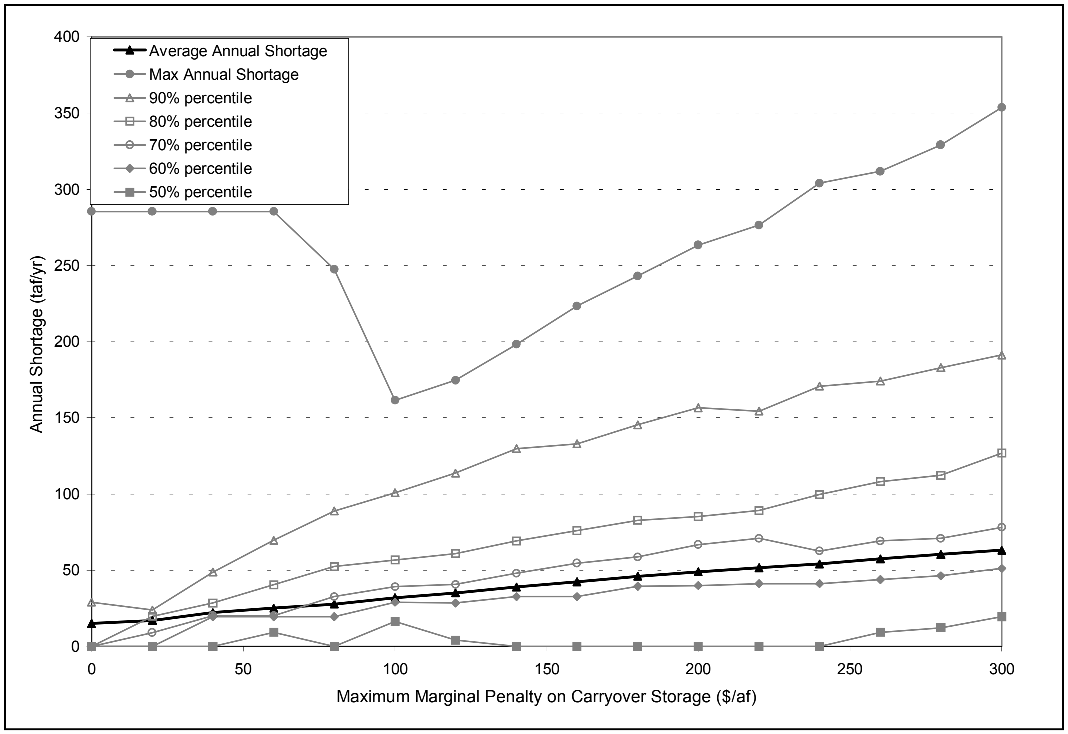

Figure 4.18 New Don Pedro Reservoir, Shortage as a Function of the Value of Carryover Storage

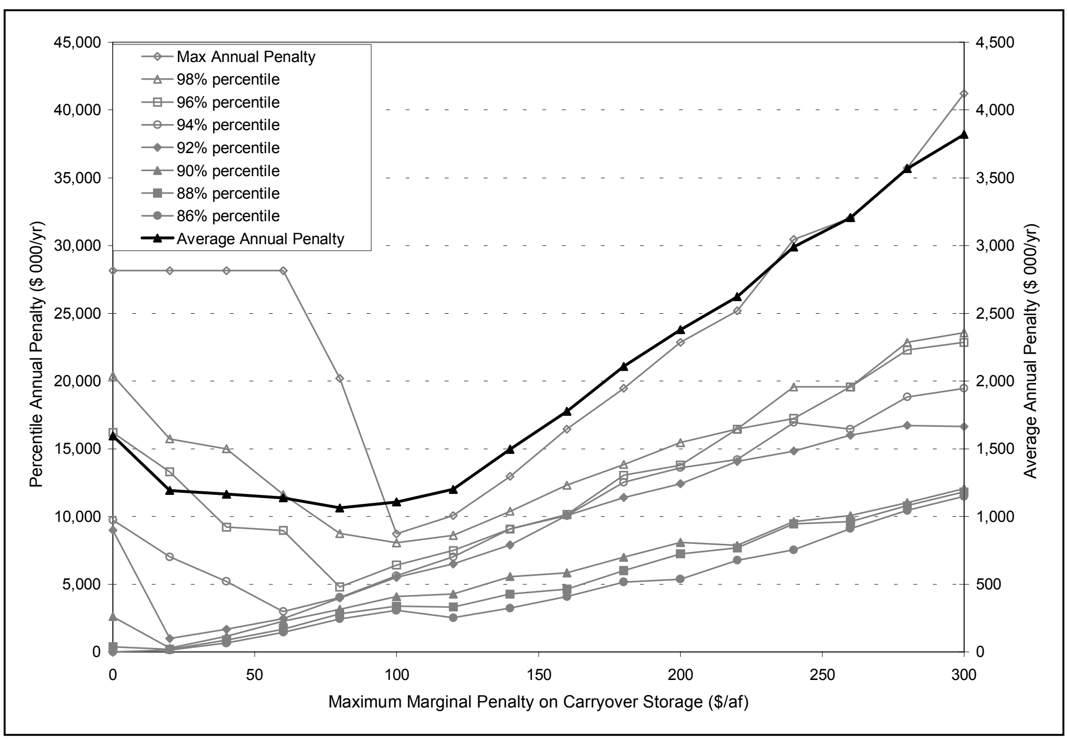

Figure 4.19 New Don Pedro Reservoir, Shortage Cost as a Function of the Value of Carryover Storage

(e) Developing Operating Rules

An important use of optimization models is the formulation of reservoir operating rules from model results. The limited foresight model should facilitate this task as reservoir operations are not distorted by perfect foresight. A rule for carryover storage could be based on the available water supply at the end of the rain flood season, i.e., storage plus the projected inflows to the end of the water year. Figure 4.20 plots the results for New Don Pedro Reservoir for the three scenarios (perfect foresight, limited foresight and myopic operation). Figure 4.21 shows a similar plot except that projected spills are deducted from the available water supply.

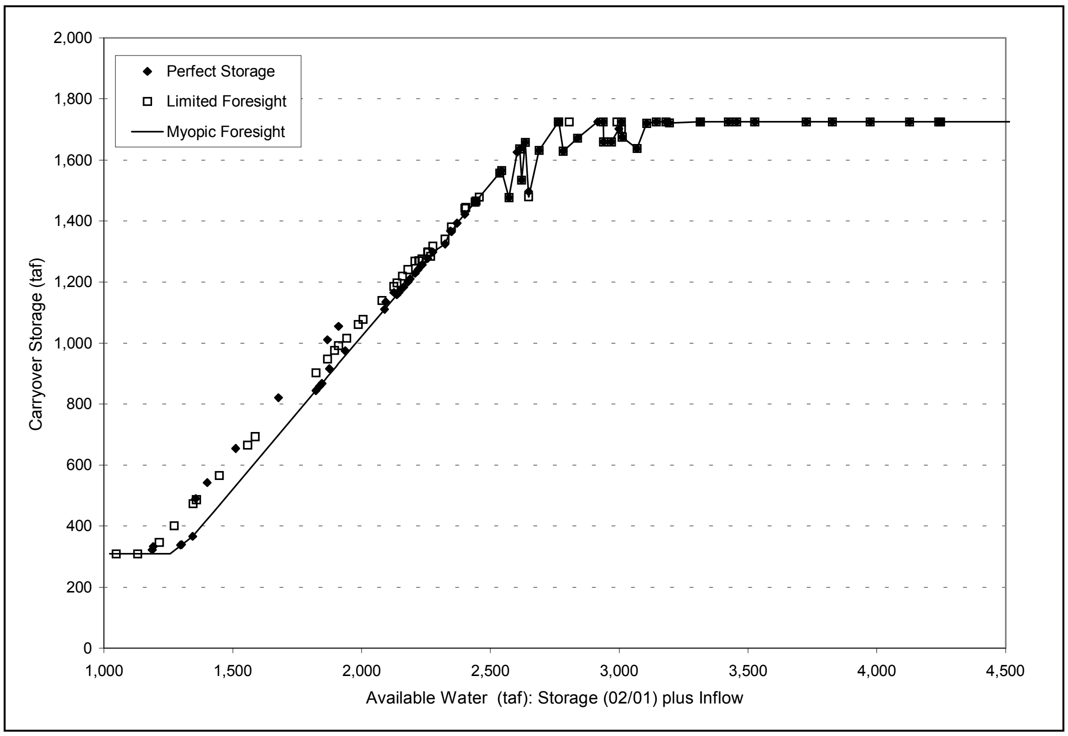

Figure 4.20 New Don Pedro Reservoir, Carryover Storage as a Function of Available Water

The rule for myopic operation is simple, once full demand is met carryover storage increases from zero at the same rate as the increase in available water supply. A rule based on the results from the perfect foresight model is less apparent. Sometimes the model hedges and sometimes it does not. In contrast, results from the limited foresight model provide a more consistent, and in this case, linear rule.

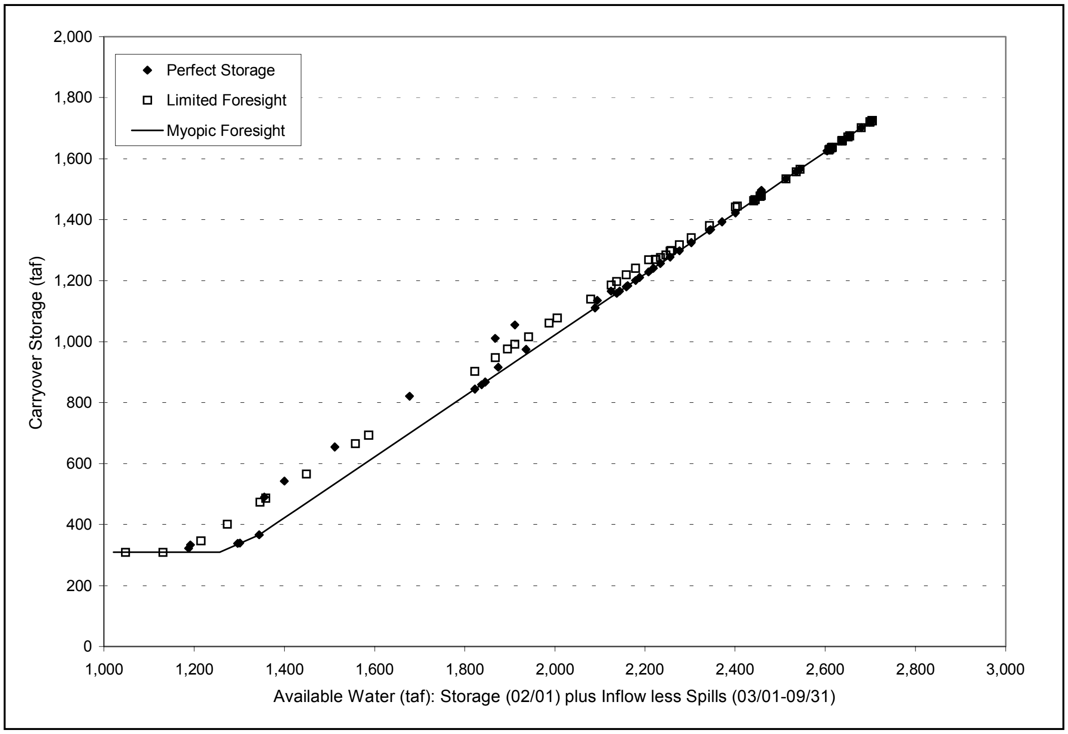

Figure 4.21 New Don Pedro Reservoir, Carryover Storage as a Function of Available Water less Spills

Alternate Stochastic Analysis

To further investigate the structure of the optimal carryover storage function, operation of New Don Pedro reservoir was formulated as a two-season SDP. The Filliben test (Filliben 1975; Loucks 1981, p189) was used to determine an adequate model for the marginal distribution of seasonal flows. A two-parameter log-normal distribution was selected. The Thomas-Fiering Markov model (Thomas and Fiering 1962) was used to represent the serial correlation between monthly flows. The recursive relationship between the log transform of flows, x, is given by:

$$x_{s,y} = \bar{x}_s + r_s \left(\frac{\sigma_s}{\sigma_{s-1}} \right) \left(x_{s-1,y} - \bar{x}_s \right) + \rho_s \left(1 - \rho_s^2 \right)^{1/2} \qquad (13)$$

where $x_{s,y}$ is the log transform of the flow in season s in year y; t is an independent standard-normal random variable with zero mean and unit variance and $\bar{x}$,σ, and ρ are the distribution parameters, i.e. the mean, standard deviation and the lag one serial correlation respectively. To provide sufficient precision, inflows and releases were discretized using a 2 taf interval.

The probabilistic relation between streamflows forms a non-stationary cyclic Markov chain. The backward-looking recursive relationship can be expressed as:

$$f_t(R_t, S_t, I_{t-1}) = C_t(R_t, S_t) + \sum_{k=0}^{n}\left[P(I_{tk} \mid I_{t-1}) f_{t+1}^{*}(S_{t+1}, I_{tk})\right] \quad (14)$$

where the state transition equation is:

$$S_{t+1} = Min(K_{t+1}, S_t + I_{tk} - R_t) \quad (15)$$

where K_t is the maximum permissible storage capacity during season t ; $C_t(R_t, S_t)$ is the immediate costs of the decision R_t (release) given state S_t (storage); $P(I_{tk}|I_{t-1})$ are the transition probabilities and $f_t(R_t, S_t, I_{t-1})$ is the cost of making release decision R_t given states S_t and S_{t-1} at stage t. $f_t(S_{t+1}, I_{t,k})$ is the cost of being in state S at stage (t+1) given the previous inflow is I_t.

Since the streamflows form an ergodic process, the optimal reservoir policy can be determined by extending the number of stages (seasons) in the SDP until convergence occurs where release decisions are independent of the ending conditions, leading to a repetition of optimal releases and a constant gain of benefits with each annual cycle. The optimal release policy is shown in Figure 4.22. As inflow during the rain-flood season is assumed to be dependent on inflow during the preceding season, the optimal release policy is a function of both storage *and* inflow, rather than a single function of the total water available (aggregated storage *plus* inflow). However as indicated in Figure 4.22, due to the weak correlation between inflows in different water years, the relative magnitude of the storage and inflow components of available water have little effect on the release rule. Compared to the operating rule derived from the limited foresight model, releases from SDP are more aggressive or less risk averse. It is considered that the cause is the difficulty in capturing the observed persistence of drought in the stochastic model. Consequently multi-year drought are of extreme low probability in the SDP model and do not warrant hedging of supplies that reduce water availability in normal years.

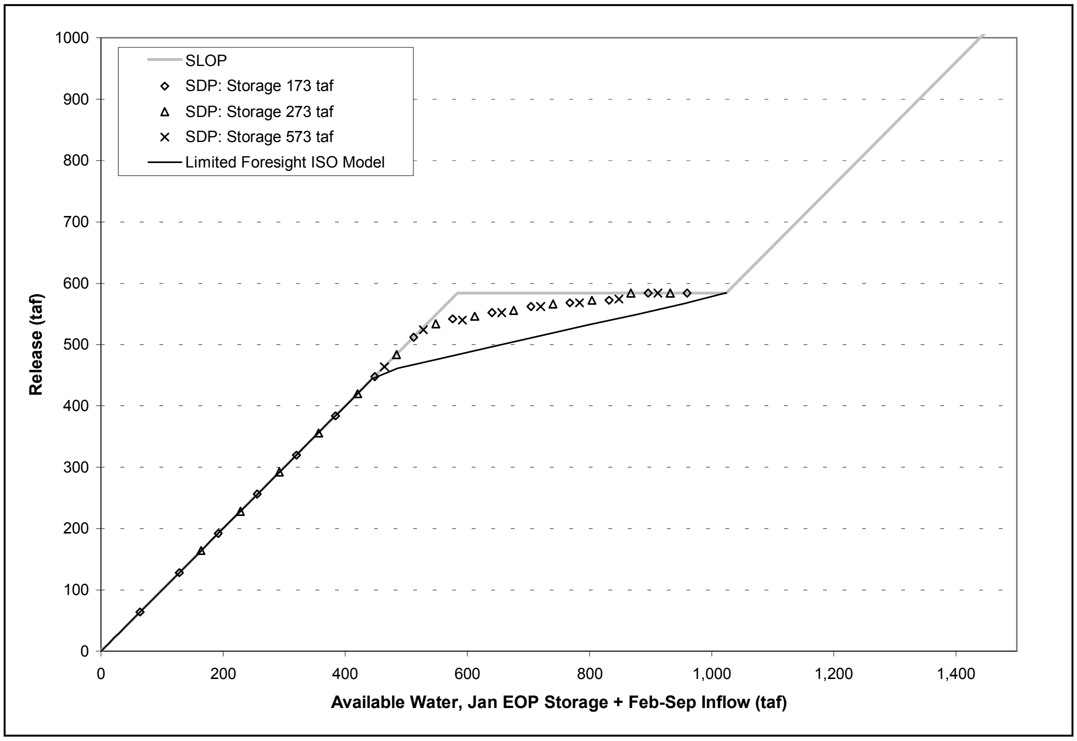

Figure 4.22 Optimal Release Policy

Summary and Conclusions

Implicit stochastic optimization (ISO) models use perfect foresight to prescribe a set of optimal reservoir operations for a deterministic hydrologic time series. Subsequently a mixture of statistical tools and engineering judgment is used to infer reservoir operating rules from model output. These rules are subsequently tested and refined using more detailed simulation models. Although this approach has been successfully applied to several 'real-world' reservoir systems, it suffers from two major drawbacks. Stakeholders not familiar with optimization methods are likely to be skeptical of models and derived policies based on omniscience. Secondly, despite attempts to use genetic algorithms, principle component analysis and artificial neural networks, there remains no easy and systematic method of deducing optimal operating rules from model results. For large systems this process is likely to be extremely time-consuming. This chapter outlines an important modification to the use of ISO models that may overcome or at least mitigate both these disadvantages. A method is described under which ISO models have only limited foresight. The time horizon for each model run and consequently the maximum horizon for perfect foresight is reduced to the current water year. Sequential model runs are linked through the initial and ending storage conditions. Penalty functions on carryover storage limit drawdown in any particular year. An iterative process is used to determine the carryover penalty function that minimizes costs over the period-of-analysis. Where the historical record is sufficiently long, or a trusted synthetic hydrology can be developed, a range of carryover storage value/penalty functions could be derived for different "year-types" based on the serial correlation of annual inflows.

The proposed limited foresight model is applied in four case studies, each consisting of a single reservoir-stream system with a single downstream demand. Optimal penalty functions are determined using a non-linear search algorithm. Comparison of results obtained using perfect and limited foresight show surprisingly little difference in reservoir operations except immediately prior to and during drought years. This is due to what is described as the 'reset' interval – the expected return period of wet conditions that limit the value of perfect information. The limited foresight model can give users greater confidence in model results by quantifying the over-achievement of perfect foresight models. Examination of model results show that general operating rules are more readily developed from the limited foresight model as reservoir operation is not distorted by perfect foresight. For one of the case studies the derived operating rule was compared with that obtained from SDP. The greater conservatism of the limited foresight rule is due to the SDP's imperfect stochastic representation of reservoir inflows and the inability of simple hydrologic models to capture the persistence of drought phenomenon.

The four presented case studies are simple single supply, single demand systems. In practice users are often supplied from a multi-reservoir system with integrated operation for greater water supply reliability. The majority of agricultural users supplement surface water supplies with groundwater pumping. The case studies consider only one beneficial use of water. Other objectives that are readily valued in economic terms may include hydropower and avoidance of flood damage. The described method for running ISO models with limited foresight therefore needs to be modified and expanded to be applicable to systems of greater complexity. It should be noted that the carryover storage penalty function probably needs to be re-calibrated when major changes are made to the system. Although, given the range of near-optimal carryover penalty functions seen for the cast studies, it is likely that optimal carryover penalty functions will not change significantly with small changes to the system.

Optimization models identify a single optimal policy. However many multi-optima or near optimal policies may exist. Rogers and Fiering (1986) advocate that optimization models be used to identify a wide range of alternative solutions that lie within the neighborhood of the surrounding optima. The exercise of judgment, and consideration of other objectives then lead to selection of a "best" policy. The limited foresight model lends itself well to this approach. A grid search identifies a range of penalty functions for which the objective function is relatively flat in the vicinity of the optimum. Results from this range of runs can be post-processed to subjectively select a compromise policy without significant change the stated objective.

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5. MULTI-RESERVOIR OPERATIONS

Introduction

Implicitly stochastic optimization (ISO) models prescribe system operations for a deterministic set of input or control variables. Though relatively easy to construct, model results are partially conditional on perfect forecasts of future inflows over the period-of-analysis. The purpose of the limited foresight model presented in Chapter 4 is to reduce the perfect foresight attribute of ISO models so to achieve more realistic operations. Knowledge of future events can be curtailed by reducing the period of optimization to a 12-month span. A set of model runs using sequential annual spans prescribes system operation over the full length of the deterministic flow record. Individual model runs are linked through starting and ending storage conditions. Ending storage represents reservoir carryover storage for the following water year. The value of water held in carryover storage is represented using a piecewise linear approximation of a quadratic penalty function on storage in the last of the 12 months. In each 12-month run, the model balances the cost of current year shortage against the cost of reducing carryover storage. An 'optimal' penalty function on carryover storage is one that results in the minimum total cost for the sum of the individual 12-month runs so that the penalty reflects the expected value of water in future use. This optimal penalty function is determined using an iterative non-linear search algorithm. Application of the technique for the analysis of a single reservoir operation (see Chapter 4) shows it provides more realistic solutions than the traditional ISO approach and less risk averse than a stochastic dynamic programming (explicitly stochastic) approach. In addition to unrealistic over-year storage operations, perfect foresight leads to misevaluation of both existing and proposed storage facilities, with two opposing effects. Perfect foresight, through the anticipation of drought, reduces shortages in dry years. This results in lower shortage costs and a lower economic incentive to build more storage. However additional storage under perfect foresight is more optimally managed compared to limited foresight so that it has greater value despite the reduction in shortage costs under perfect foresight.

Two parameters are required to define the optimal quadratic penalty function for any single reservoir. Application of the limited foresight model to a multi-reservoir system would require a multi-dimensional parameter search that would quickly exhaust all but the most patient of investigators. This chapter presents a modification to the limited foresight model to reduce the dimensionality of multi-reservoir problems. A non-linear search is used to identify the value of total system or aggregated carryover storage. Derived (optimal stochastic) balancing rules are subsequently used to disaggregate the aggregate storage-value relationship into individual penalty functions for each reservoir. The method is applicable to a system of parallel reservoirs, whereby reservoirs located on different streams supply a common downstream demand. A simple case study is presented and the results compared to those obtained from a more rigorous multi-dimensional search.

Reservoir Balancing Rules

Operating Rules

Reservoir operation is guided by rules that prescribe the "apportionment (of storage) among reservoirs, among purposes and among many time periods" (Bower et al. 1962). A diverse set of rules for single-purpose reservoir systems in series and in parallel are derived by Lund and Guzman (1999). Purposes include water supply, flood control, hydropower, water quality and recreation. In general rules are formulated in terms of the past and current state of the system (e.g. current storage, current, past and forecasted inflows and past deliveries). For monthly planning studies some rules may be predetermined, e.g., rule curves for monthly flood control and minimum operating levels. Other rules must be determined, such as balancing storage between reservoirs and decisions on carryover storage targets for over-year operations.

Reservoirs in Parallel

A large literature exists on the theoretical operation of reservoirs in parallel (Lund and Guzman 1999). Sand (1984) analytically derived an optimal release policy for a simple three-period parallel reservoir system operated for water supply assuming time-independent flows and a common downstream demand. Results suggested that the critical event is for one reservoir to be full and spilling while others in the system remain unfilled followed by a subsequent shortage before all reservoirs fill again. Sand's work suggests that a reasonable operating policy for the refill cycle is to minimize expected spills, to avoid this inefficient condition.

<u>Space Rule</u>

Bower et al. (1962) describe a space rule for the drawdown of a set of parallel reservoirs supplying a common downstream demand. It is assumed that reservoir spills are not productively used and are lost to the system. The objective of the space rule is to minimize the expected value of system-wide spills. This is equivalent to equalizing the probability that reservoirs will refill by the end of the refill season. The space rule states that spills can be minimized by apportioning storage during the refill cycle so that the ratio of space available in each reservoir to that in all reservoirs equals the ratio of the predicted inflows to each reservoir during the remainder of the refill cycle to that in all reservoirs. Mathematically this can be stated as:

$$\frac{\left(K_i - S_{fi}\right)}{\sum_{i=1}^{n}\left(K_i - S_{fi}\right)} = \frac{EV[CQ_i]}{\sum_{i=1}^{n} EV[CQ_i]}, \quad \forall i \qquad (1)$$

where K_i is the storage capacity of reservoir *i* (assumed to be constant), S_{fi} is the end-of-period storage for the current period and CQ_i is the cumulative inflow from the end of the current period to the end of the refill cycle. The space rule requires: (a) that accurate short-term forecasts are available during the refill cycle so that reservoir releases can be correctly apportioned; and (b) that demands during the refill period are sufficiently large to allow storages to be constantly adjusted according to the rule. The effectiveness of the space rule is a function of the coefficient of variation of the mean monthly flows, the correlation of flows between streams and forecast reliability. A greater degree of forecast accuracy is required towards the end of the refill cycle.

The space rule can be used to specify month-to-month releases during the refill cycle or target storages at the end of the drawdown cycle. Releases may not always be feasible due to operating constraints. The space rule may specify negative releases for some reservoirs (Johnson et al. 1990). Where heuristic guidelines cannot be followed precisely, it has been general practice to adhere to them as closely as possible (Stedinger et al. 1983). Loucks and Sigvaldason (1982) and Yeh (1985) review other approaches.

New York City Rule

The New York City (NYC) rule, developed by Clark (1950) attempts to minimize spills from a set of parallel reservoirs during the refill season. For operation of the New York City water supply Clark derived a set of control curves that indicate the refill potential of each reservoir for a given shortage level during the year. The NYC rule is implemented by:

> "*increasing (if possible) or decreasing the draft from one of the watersheds in order to equalize storage with the other (with reference that is, to the percentage year). By this method, the reservoirs in each of the watersheds have the same chance of filling by the succeeding June 1*" (Clark 1956).

The NYC rule is based on the probability of the spills rather than actual volumes, as used for the space rule. The rule can be derived by solving the optimization problem with the objective (function) of minimizing the expected value of spills, Z, from all *n* reservoirs.

$$Min\ \ Z = EV\left[\sum_{i=1}^{n} \min(0, S_{fi} + CQ_i - K_i\right] \qquad (2)$$

subject to: $$\sum_{i=1}^{n} S_{fi} = \sum_{i=1}^{n} \left(S_{oi} + Q_i\right) - D \qquad (3)$$

where D is the total (common) downstream demand during the period, S_{oi} is the beginning-of-period storage for reservoir *i*, and Q_i is the inflow during the current period (assumed to be known). Constraint (3) states that all demands must be met, which is usually not a problem during the refill portion of the year. This set of equations determines the release pattern for each reservoir and the storage at any period. Expressing the expectation as an integral over the probability density function of CQ_i, the first-order optimality conditions give:

$$P_r\left[CQ_i \geq K_i - S_{fi}\right] = \lambda \qquad (4)$$

This is the usual form of the NYC space rule. The probability of spills, λ, is equal to the Lagrange multiplier on the constraint expressed in (3). These relationships have previously been derived by Sands (1984) and Johnson et al. (1991). For a concise derivation see Lund and Guzman (1999). The values of S_{fi} that satisfy (4) may not be feasible, requiring negative storage.

The space rule is a restricted case of the more general NYC rule and is applicable when stream inflows to each reservoir have the same distributional form (*f*) but are scaled by their expected value (Sand 1984):

$$\frac{f_{CQ_i}}{EV[CQ_i]} = \text{constant}, \forall i \qquad (5)$$

Parametric Rule

Balancing rules can often be parameterized in the linear form:

$$S_{fi} = a_i + b_i V$$

where a_i and b_i are unknown parameters and V is the total system storage at the end of the current time step. For a system of N reservoirs there are 2(N-1) unknowns as $\sum_{i=1}^{N} a_i = 0$, and $\sum_{i=1}^{N} b_i = 1$. Nalbantis and Koutsayiannis (1997) show that this parametric form is applicable to a range of system configurations and a range of objectives that include minimizing spills, minimizing evaporation and seepage losses, and ensuring supplies for side demands. Lund and Fierra (1996) find piece-wise linear forms to be commonly arise from large-scale multi-purpose reservoir optimization results.

Optimization and Balancing Rules

Several authors have used heuristic and derived operating rules to simplify multi-reservoir operating problems. Archibald et al. (1997) used the "equally full heuristic" to disaggregate prescribed optimum release from an aggregate reservoir system. The heuristic attempts to maintain the ratio of active storage to storage capacity the same for all reservoirs. Though this rule is applied to hybrid reservoir configurations, the authors give no arguments for its validity.

Development of Penalty Functions for Carryover Storage

The limited foresight model is based on identifying functions for the value of carryover storage. A cost minimization formulation requires that these values are expressed in terms of a concave penalty, i.e., carryover storage shows diminishing marginal value. In most climates, reservoirs undergo distinct cycles of refill and drawdown. Typically precipitation is unimodal. In the Western US, cold wet winters are followed by hot dry summers. In principally agricultural regions demands on the system are low in the winter and peak in late summer. Where reservoirs provide flood control any excess storage must be released in the late fall/early winter to create flood control space for the rain-flood season.

For parallel reservoirs operated for over-year storage, releases during the summer are balanced to achieve subsequent target carryover storages for each reservoir. From fall through to the end of the rain-flood season demands are relatively low, limiting the ability of operators to adjust storage between reservoirs. Where watersheds are at sufficient elevation, peak stream flows (and consequently reservoir inflows) occur in the late spring or early summer driven by snowmelt. The snowmelt hydrograph typically has a broad base and is relatively constant over a period of several months. Although peak flows are generally less than during the rain-flood season, the duration and consequently the volume of inflow during snowmelt can be far greater. In wet years, reservoir releases for flood control may be sustained over several months and are much more significant in terms of total volume. Given relatively reliable forecasts and the steady nature of the inflow, reservoir operators are able to adjust flood releases so that the reservoir just fills at the end of the flood control season.

Penalty Function for Aggregate Reservoir Carryover Storage

Consider a penalty function for aggregate carryover storage. The function is assumed to be convex, quadratic and have a known upper limit at which the value of additional carryover storage is zero. For a system of n parallel reservoirs with a common downstream demand, this upper limit is given by:

$$K_{\max_{aggregate}} = \sum_{i=1}^{n} \left[K_i - V_{RFCP_i} - V_{\min i} + Min\left(\sum_{t=1}^{T} I_{i,t} \right) \right] - \sum_{t=1}^{T} D_t \qquad (6)$$

where K_i is the physical capacity of reservoir *i*, V_{RFCP} is the rain flood control pool, V_{min} is the minimum operating storage, I_t is the reservoir inflow in month t, T is the last month of the rain flood season and D_t is the deterministic total downstream demand in month t. The last term in the square bracket in equation (6) represents the minimum total inflow from the start of the water year to the end of the rain flood season if demands are to be met. For a deterministic model this can be set equal to the minimum inflow over the period-of-analysis.

Disaggregation of Aggregate Penalty Function

For a set of parallel reservoirs, the space rule given by equation (1) can be re-arranged to express the required end-of-period storage for reservoir *i* that minimizes the expected value of spills:

$$S_{fi} = K_i - \left(\sum_{i=1}^{n} K_i - V \right) * \frac{EV[CQ_i]}{\sum_{j=1}^{n} EV[CQ_j]} \qquad (7)$$

Consider a system of n parallel reservoirs that have filled during the refill season. At the start of the drawdown season releases for demand will initially be met from all n reservoirs in accordance with equation (7) until one of the reservoirs reaches its minimum operating level. Demand will subsequently be met from (n-1) reservoirs. In an extreme drought reservoirs could be successively emptied until demand is met from a single reservoir. Let the point at which reservoir *j* reaches its minimum operating level be termed a break-point. From equation (1) the storage in reservoir *i* corresponding to the break-point for reservoir j can be calculated as:

$$S_{fi} = K_i - K_j \frac{E[CQ_i]}{E[CQ_j]} \qquad (8)$$

where reservoir i has a lower refill potential than reservoir *j*. For n reservoirs there are (n-1) break-points. Aggregate storage is distributed among m reservoirs according to the following equations:

$$S_{fi} = K_i - EV[CQ_i]* \frac{\sum_{i=1}^{m} K_i - V}{\sum_{i=1}^{m} EV[CQ_i]} \qquad (9)$$

where K_i and S_{fi} are measured above minimum operating level and m is the number of reservoirs that are being filled/drawn down. Under a system of penalties (P_i) for carryover storage, reservoirs will be simultaneous drawn down where the first derivatives of their penalty functions is equal, and equal to that of the aggregate penalty function for the system. Let the last reservoir to be drawn down be denoted as *i* and the second to last be denoted as *i*+1. Then:

$$S_{fi} = V \quad \text{and} \quad P_i = P_{agg} \quad \text{for } 0 \le V \le K_i - K_{i+1} \frac{EV[CQ_i]}{EV[CQ_{i+1}]} \qquad (10)$$

where *P* denotes the penalty. Let $V_{BP(i+1)}$ represent the right-hand side upper bound in equation (10). For solution by LP all penalty functions must be piecewise linear so that subsequent disaggregate storage and penalties can be calculated as:

$$S_{fi} = V_{BP(i+1)} + \frac{(V - V_{BP(i+1)})}{EV[CQ_i] + EV[CQ_{i+1}]}.EV[CQ_i] \text{ for } V_{BP(i+1)} \le V \le V_{BP(i+2)} \qquad (11)$$

$$S_{fi+1} = \frac{(V - V_{BP(i+1)})}{EV[CQ_i] + EV[CQ_{i+1}]}.EV[CQ_{i+1}] \text{ for } V_{BP(i+1)} \le V \le V_{BP(i+2)} \qquad (12)$$

$$P_i = \int_{V_{BP(i+1)}} \frac{\partial P_{agg}}{\partial S_{agg}}.\partial S_{fi} + P_{BP(i+1)} \qquad (13)$$

$$P_{i+1} = \int_{V_{BP(i+1)}} \frac{\partial P_{agg}}{\partial S_{agg}}.\partial S_{fi+1} \qquad (14)$$

Case Study

The method outlined above describes how reservoir balancing rules may be used to reduce the dimensionality of the non-linear search needed for the limited foresight model when applied to a multi-reservoir system. To test the validity of this approach a parallel two-reservoir system is considered. New Don Pedro on the Tuolumne River and Lake McClure on the Merced River are multi-purpose reservoirs operated primarily for agricultural water supply in the San Joaquin Valley of California. The independent operation of these two reservoirs is analyzed in Chapter 4. A hypothetical case is now considered whereby additional conveyance is provided so that both demand areas can be supplied from either reservoir. This situation is illustrated in Figure 5.1.

Validity of Space Rule

The space rule for balancing storage operations is based on the expected value of inflows. Its validity requires that flows have the same probability density function when normalized by their mean (Lund and Guzman 1999). Figure 5.2 shows the probability density function for the annual inflows to New Don Pedro reservoir and Lake McClure assuming they are lognormally distributed. The distribution parameters were fitted using the method of moments. The similarity in the annual flow distributions is due to the proximity of their watersheds in the Sierra Nevada Mountains. The probability distribution function for the Merced River is more positively skewed with a slightly narrower range of flows around the mean. This may reflect the absence of upstream flow regulation that influences inflow to New Don Pedro on the Tuolumne River.

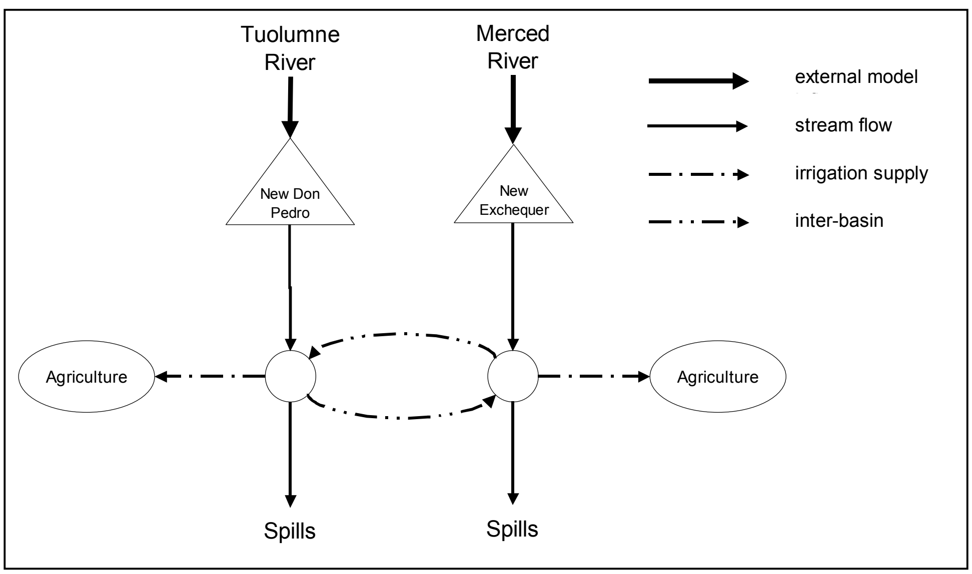

Figure 5.1 Hypothetical Parallel Two Reservoir System

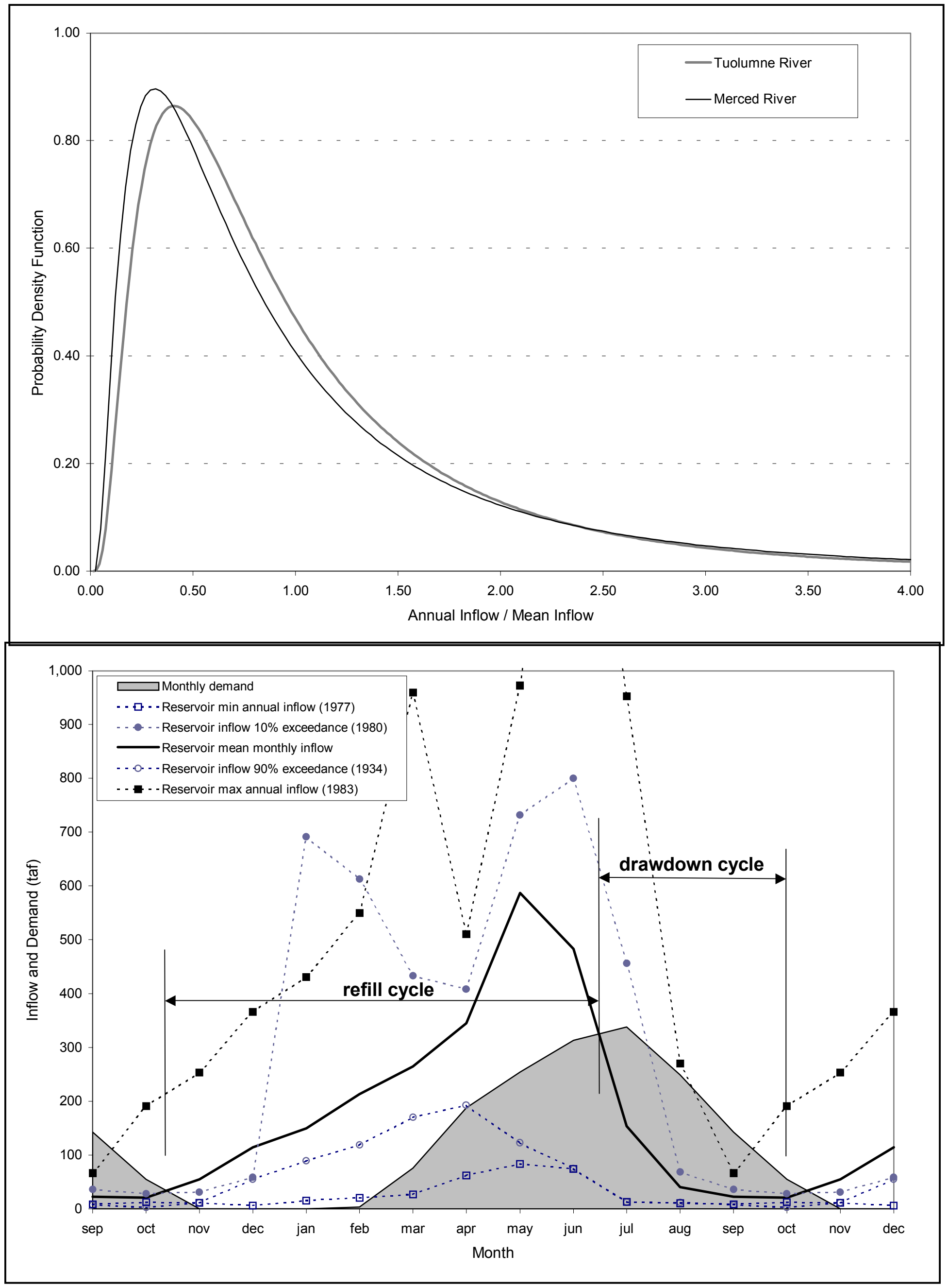

Figure 5.2 Probability Density Function for Reservoir Inflows

Drawdown and Refill Cycles

Figure 5.3 compares monthly system inflow to monthly demand for the whole system. Refill and drawdown cycles vary from year-to-year. Under average inflow conditions the refill period stretches from approximately mid-October to mid-June.

Figure 5.3 Reservoir Refill and Drawdown Cycles

Space Rule and Flood Control

It is assumed that the critical period to be considered when applying balancing rules to allocate carryover storage is from the fall to the end of the rain-flood season when flood space requirements are at their greatest. Though spills during the subsequent snowmelt are significant, operators have much greater ability to readjust storage between reservoirs due to the increase in demand. Although K_i is not constant, the space rule is still valid up to the end of the rain-flood season as values of K_i are either constant or decreasing and demands are low. For the two reservoirs in the case study this period is from 1st October to 28th February.

Model Runs

Three scenarios are considered: reservoir operation under: (a) perfect foresight; (b) limited foresight; and (c) myopic operation. Under myopic operation, managers do not consider the effect of current releases on the ability to meet demand in future years. Releases therefore follow the standard linear operating policy (SLOP). For the limited foresight scenario the model is solved using two alternative approaches. First, a four-parameter search is undertaken using the Nelder-Mead simplex method to separately define optimal carryover storage penalty functions for the two reservoirs. In the second approach an optimal aggregate penalty function for the two reservoirs is determined using a two-parameter search. The aggregate penalty is disaggregated into separate penalty functions for the two reservoirs using the storage balancing rules defined by equations (11) to (14).

Results

Results for the three scenarios are summarized in Table 5.1. For all scenarios integrated reservoir operation, achieved through additional conveyance, reduces shortages and shortage costs. Reductions in shortage are of the order of 25%, reduction in costs varies from 3% for the myopic model to 12% under limited (two-parameter search) and perfect foresight. Integrated operations also substantially reduce the value of capacity expansion predicted by the limited foresight and myopic models.

Of most interest are the differences between the two-parameter and four-parameter search for the limited foresight model. As expected, the four-parameter search yields a slightly more efficient operation with shortages down 5% and costs down by 6% compared to the two-parameter search combined with balancing rules. Figure 5.3 shows the resulting carryover storage penalty functions obtained using the two methods.

Table 5.1 Model Results for a Parallel Two-Reservoir System

Time Horizon for Optimization	Average Annual Shortage (taf)			Average Annual Shortage Cost ($million/yr)			Av. Annual Shadow Price on Reservoir Capacity ($/af/yr)		Av. Annual Shadow Price on Trans-basin Conveyance ($/af/yr)	
	NDP[1]	NE[2]	Total	NDP[1]	NE[2]	Total	NDP[1]	NE[2]	NE to NDP	NDP to NE
Isolated Operation										
Perfect Foresight	24	18	42	558	1,232	1,790	2	6	90	0
Limited Foresight	44	27	71	1,064	1,944	3,008	10	45	100	0
Myopic	24	18	42	1,595	2,622	4,217	52	83	112	0
Integrated Operation										
Perfect Foresight	20	12	32	979	587	1,566	4	4	0	0
Limited Foresight - 4PS	33	20	53	1,551	923	2,474	7	7	0	0
Limited Foresight - 2PS	35	21	56	1,650	992	2,642	7	7	0	0
Myopic	20	12	32	2,546	1,528	4,074	0	0	0	0

Notes: 1 New Don Pedro Dam and Reservoir on the Tuolumne River
2 New Exchequer Dam and Lake McClure on the Merced River

The four-parameter search results in an aggregate penalty function with greater curvature than the quadratic form assumed for the two-parameter search. The increase in curvature results in high penalties at low storage while maintaining low penalties at higher storages. This translates into reduced hedging in most normal to dry years but increased hedging during critical years. The four-parameter search is able to achieve this by assigning a relatively flat penalty function for the larger New Don Pedro reservoir and a steep penalty function for the smaller Lake McClure. Despite these differences reservoir operations under the two and four-parameter searches are very similar. Figure 5.5 shows the aggregate carryover storage for water years 1921-1994. In all but the driest conditions (1990-1993) total carryover storage under the two-parameter search is equal or marginal higher than the four-parameter search. Figures 5.6 and 5.7 show that storage operations under the two-parameter search lie closer to those of perfect foresight than the four-parameter search. Figure 5.8 compares the annual shortage costs. The greatest difference occurs between 1990-1993. For the first two of these three years the two-parameter method provides lower costs. Only in 1993 after five years of drought does the four-parameter search significantly out-perform its two-parameter counterpart.

An interesting check on the general validity of the assumed balancing rules is to examine the assignment of carryover storage between the two reservoirs under perfect foresight. The September end-of-period available storage (as measured from the February bottom of flood control space) divided by the mean October-February inflow is a measure of the reservoir refill potential. If the balancing rule does minimize spills then values of this measure should be the same for New Don Pedro reservoir and Lake McClure. The plot is shown in Figure 5.9. The solid line shows the relationship ascribed by the space rule. Although there is a large degree of scatter, the 73 values assigned under perfect foresight generally follow the space rule.

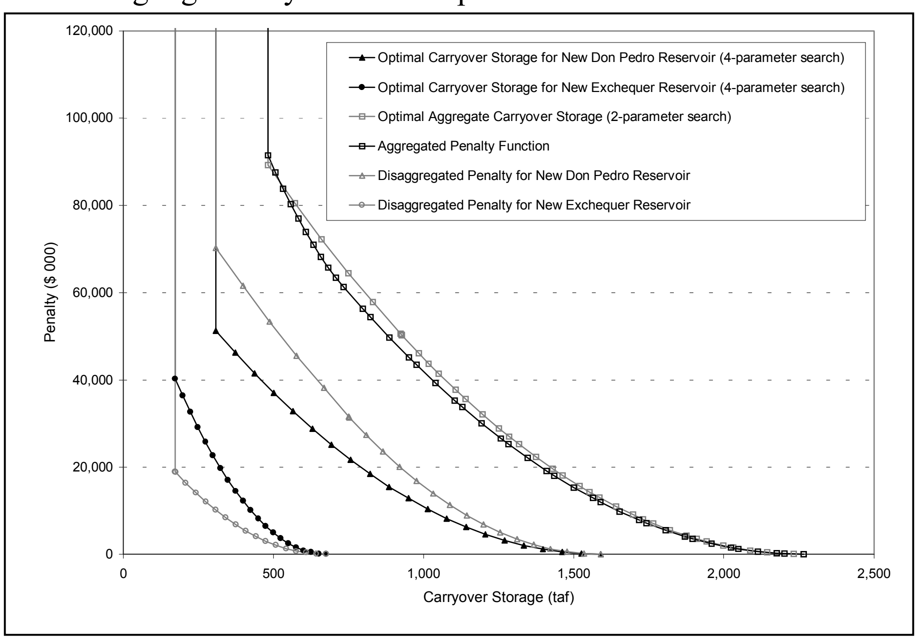

Figure 5.4 Carryover Storage Penalty Functions

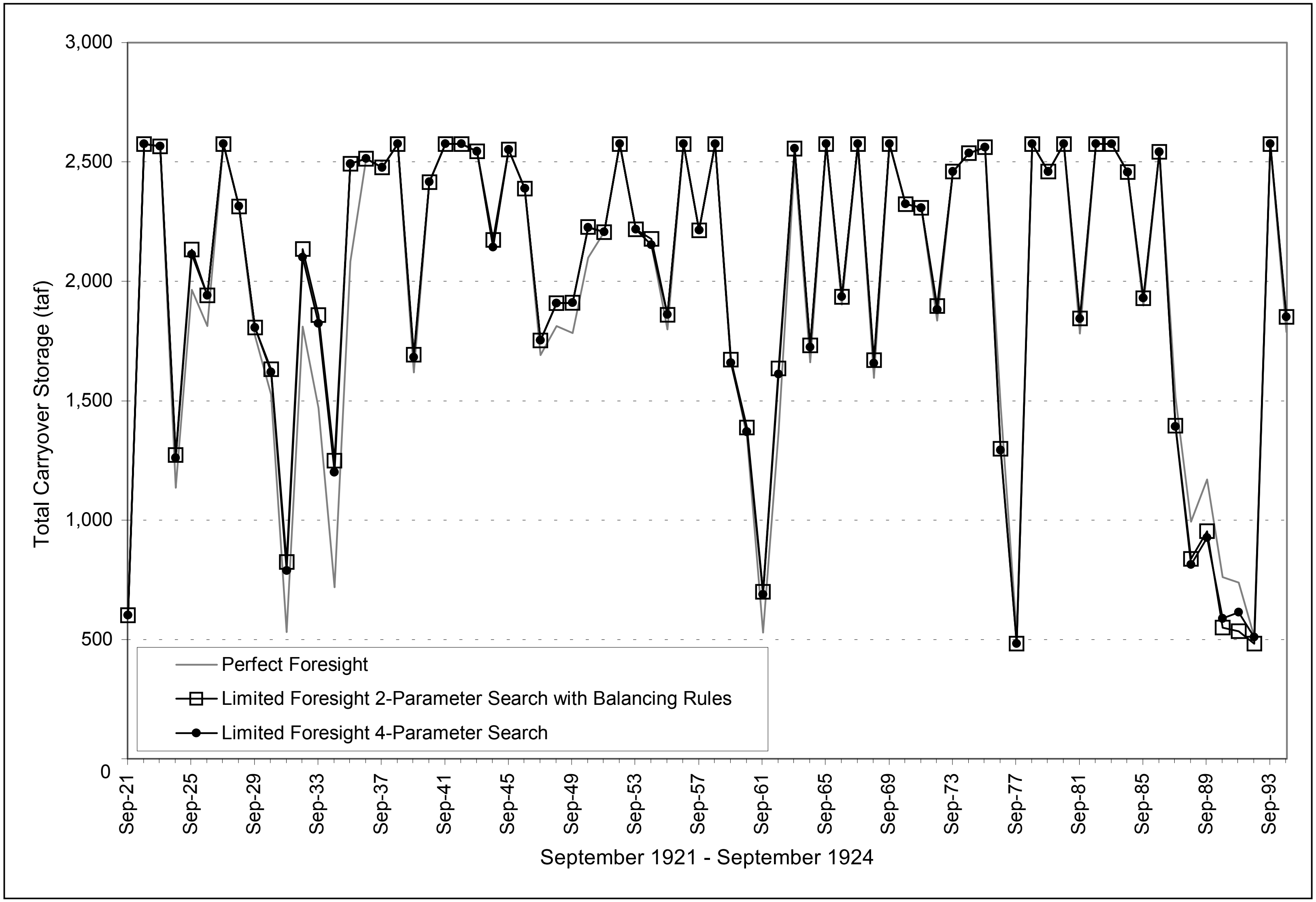

Figure 5.5 Aggregate Carryover Storage

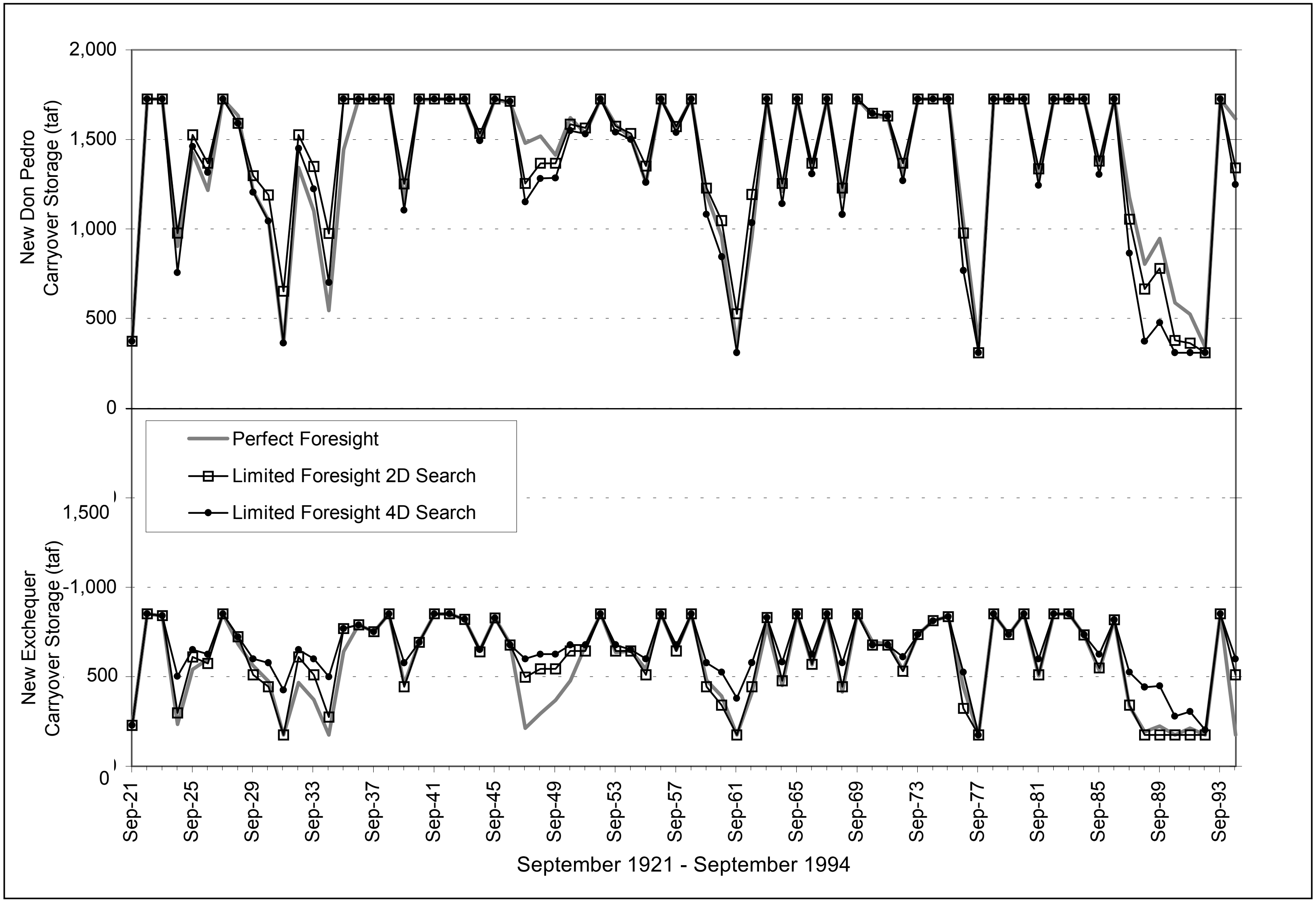

Figure 5.6 Disaggregate Carryover Storage

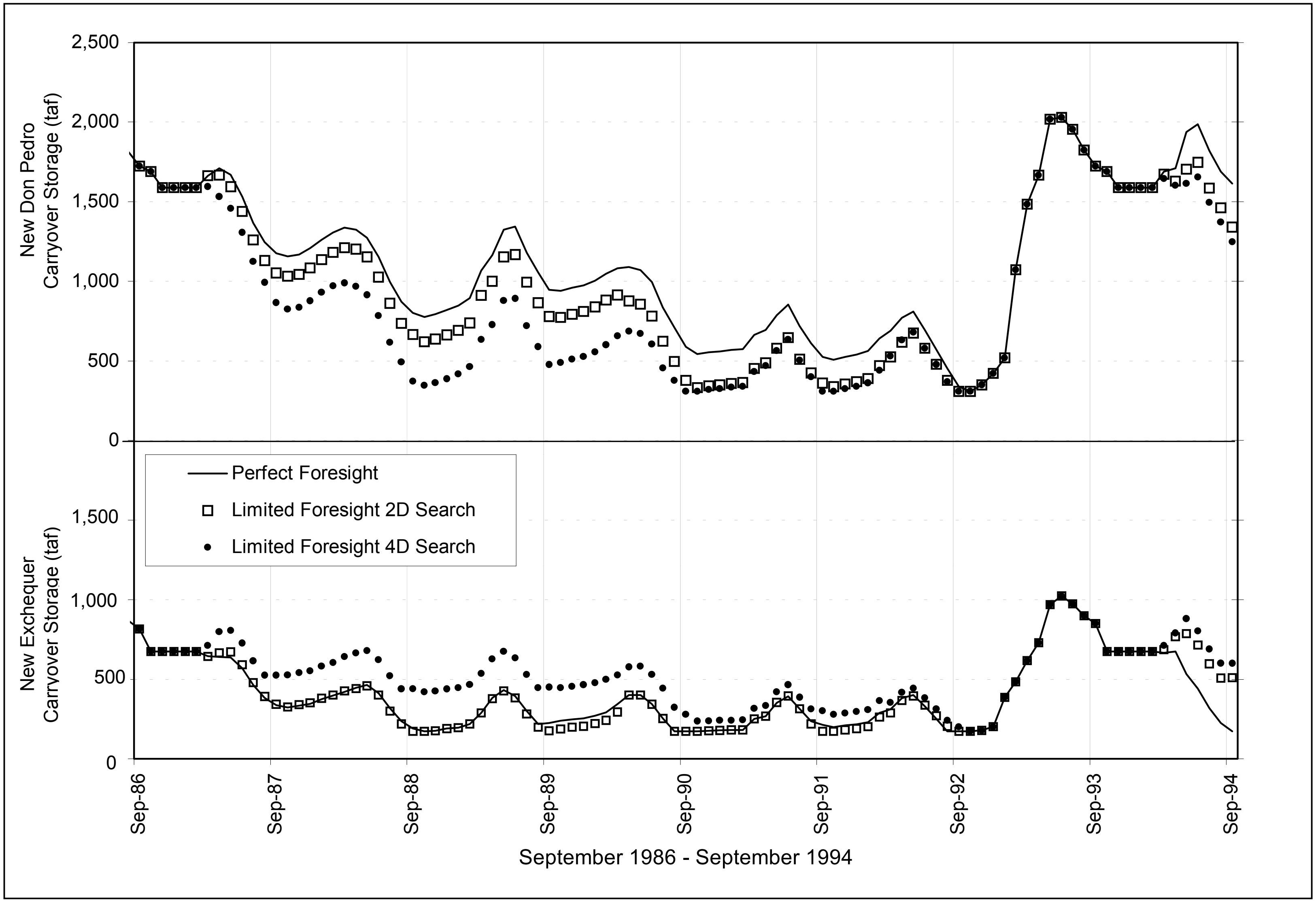

Figure 5.7 Monthly End-of-Period Storage

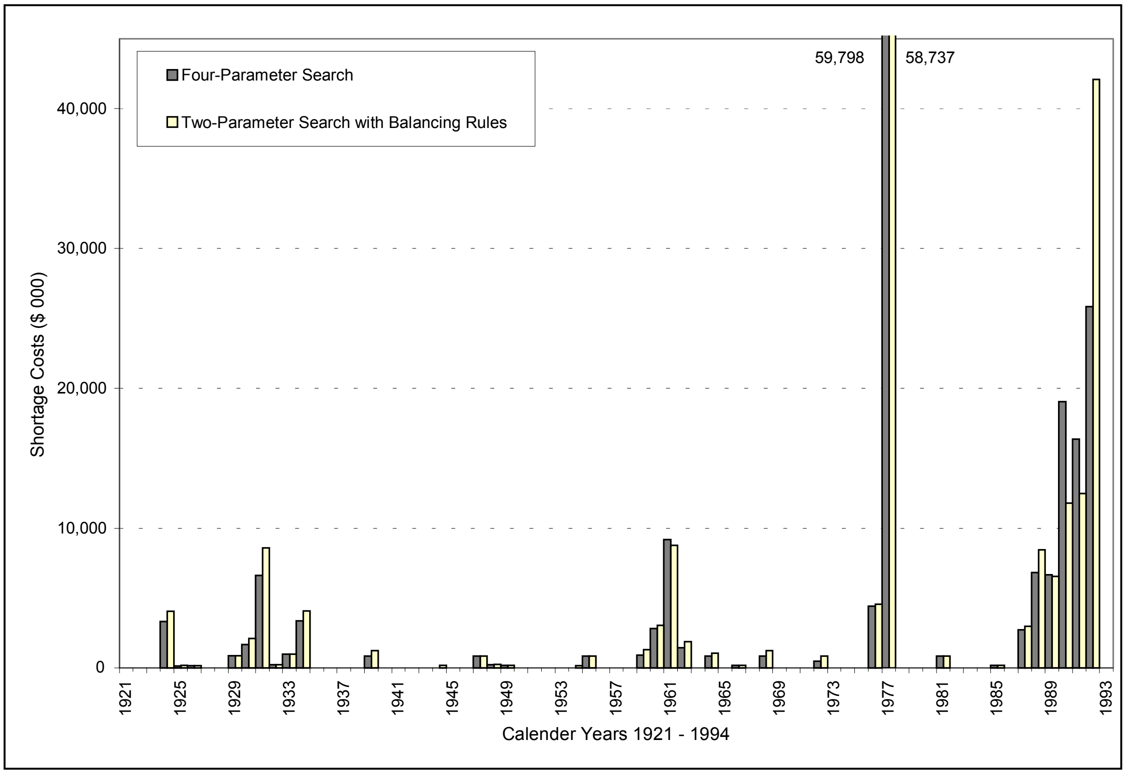

Figure 5.8 Annual Shortage Costs

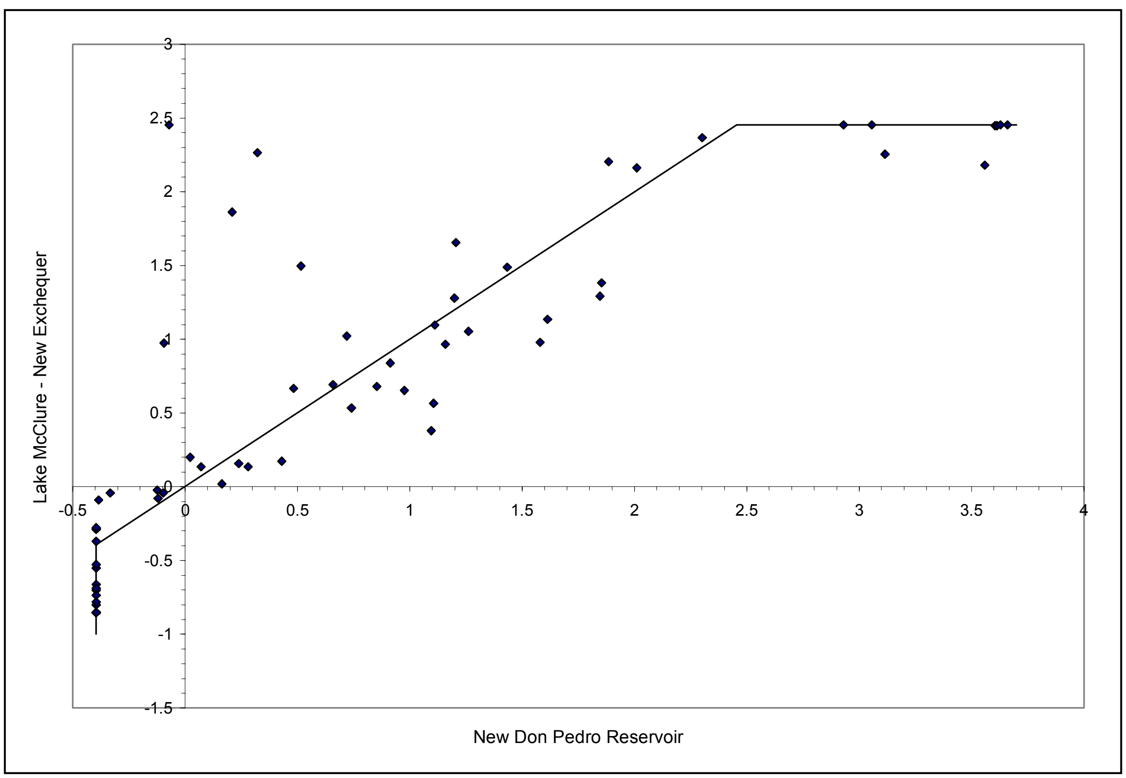

Figure 5.9 Ratio of Available September Storage to Mean Inflow under Perfect Foresight

Summary and Conclusions

The use of reservoir balancing rules allows a practical extension of the limited foresight model to the analysis of more complex multi-reservoir systems. A non-linear search is used to identify the value of system-wide or aggregate carryover storage. Balancing rules that aim to minimize the expected value of spills are subsequently used to define individual carryover storage penalty functions for each reservoir. A simple case study of two parallel reservoirs was used to compare (a) this approach to (b) the more rigorous multi-parameter non-linear search required to identify individual penalty functions directly. The two different methods resulted in very similar reservoir operations. Storage values only significantly diverged in the last year of a six-year drought. The multi-parameter search resulted in slightly superior reservoir operations with 6% less shortage costs. This cost difference is small compared to those of the perfect foresight and myopic models that are 59% and 154% of the limited foresight model. It is argued that differences in the carryover penalty functions between the two approaches are due to the assumption that the value of aggregate storage is quadratic in form rather than limitations of the balancing rules.

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6. OPTIMIZATION AND CONJUNCTIVE GROUNDWATER MANAGEMENT

Introduction

Water supply reliability and system resilience to drought can be analyzed in terms of the stock and flow characteristics of the system. Systems where flows are a large fraction of available stocks are more vulnerable to disruption (NHI 1997, p2). Diminishing water supply fluctuations requires increased storage capacity. However, surface storage has long been out of favor due to increasing environmental concerns. In comparison to surface storage, groundwater offers vast storage reserves. Water storage in aquifers for conjunctive use is especially attractive because it "results in less evaporation, has a lower capital cost, usually does not require an extensive distribution system, and is generally more environmentally acceptable than surface storage" DWR (1987, p47). But the use of groundwater storage is not without controversy. It has long been regarded as a resource for the sole use of overlying landowners. Its use as an integrated element in a regional or statewide supply system has met local resistance. Over-extraction can result in land subsidence and water quality degradation. It is likely, however, that conjunctive use of groundwater is one of the most economic and environmentally benign methods of improving system reliability.

Despite the numerous calls for greater conjunctive use, until recently there has been a surprising lack of case studies in the technical literature that consider the impact of conjunctive use on reservoir management and in particular on reservoir operating rules. State and federal agencies have often ignored groundwater conjunctive use when planning and operating surface reservoir systems (Hundley 1992, Lall 1995). Regional planning and operations models usually are restricted to the surface water system. Groundwater management models usually are typically restricted to local problems of hydraulic management (e.g., Andricevic and Kitanidis 1990, Danskin and Freckleton 1992) or conjunctive use of stream-aquifer systems (e.g., Young and Bredehoeft 1972). Most texts on reservoir operation ignore the subject (e.g., Loucks, et al. 1981; Mays and Tung 1992, ReVelle 1999). Perhaps this indicates the considerable political and institutional barriers to integrating local groundwater resources into a regional supply system.

While mathematical models can aid conjunctive use planning, model results should be interpreted in light of their limitations. Too much emphasis is placed on their predicative capacity rather than their use as a tool to better understanding the response of the system. The many aspects of integrated groundwater surface-water operations prohibit their detailed representation in most conjunctive use models (El-Khadi 1989). Conjunctive use advocates often use simple 'put and take' models, but without subsequent detailed analysis the impacts and even feasibility of conjunctive use cannot be fully determined. Conjunctive use models should account for the stochastic nature of surface flows. A monthly rather than annual time step is preferable so as to capture both inter-season and inter-annual uncertainty, and the effects of monthly varying surface flood-storage constraints. Economic rather than yield objectives are preferable. The nonlinear nature of shortage costs makes hedging an important aspect of reservoir operation through the assignment of carryover storage. Risk avoidance may influence local operations, however most probabilistic models use expected value criteria. Groundwater pumping costs are nonlinear, being both flow and head dependent. Management objectives may include control of groundwater levels, but accurate representation of well piezometric levels requires a spatially detailed representation of groundwater.

This chapter briefly reviews conjunctive use operations and associated legal and institutional problems. This is followed by a discussion of groundwater management models. Attention is focused on dynamically representing groundwater in reservoir operation models to better integrate operation of both resources.

Conjunctive Use

Operation

Conjunctive use is a comprehensive water management program that co-ordinates surface and groundwater operation. Unfortunately, the inscrutable physical and legal nature of groundwater makes central planning difficult. Groundwater basins have ill-defined limits, natural recharge cannot be measured directly and records of groundwater use are seldom complete. The lack of data for groundwater is compounded by the absence of state or federal requirements for quantification of the resource. Efficient electric pumps and cheap energy provided the catalyst for intensive groundwater development. Much of groundwater is extracted by individuals and is not regulated or managed by local agencies. In many agricultural areas supplied by surface water, underlying aquifers are recharged primarily from irrigation return flows. In this situation groundwater often acts as a contingent water source used in dry years to buffer variations in surface water supplies.

Managed development of groundwater has focused on the notion of 'safe-yield' and 'mining'. However these simple concepts ignore the dynamics of the system and have resulted in water policies that deplete groundwater, dewater streams and damage wetlands (Sophocleous 1997, Bredehoeft 1997). Under natural conditions groundwater basins are in long-term equilibrium; recharge is balanced by aquifer discharge to streams and springs. Groundwater pumping may initially deplete the aquifer but if groundwater levels are to stabilize extraction must be balanced by long-term increases in induced recharge or decreases in aquifer discharge. The Water Resources Council (1973) recommends the use of the term "optimal yield" to replace safe-yield and mining. Optimal yield is defined as "the planned use of groundwater so as to maximize economic benefits subject to physical, chemical, legal and other constraints". Optimal yield is a function of time and system state variables, including storage.

The success of conjunctive use lies in exploiting differences in the characteristics of surface and groundwater flows. In the Western US, surface water is available seasonally from winter rain and spring snowmelt. However, the timing and volume vary considerably from year to year. Periods of low streamflow often coincide with periods of peak demand. It is possible to determine the size of surface storage required to regulate the supply with the desired reliability. However, provision of this surface storage may be uneconomic or raise environmental concerns. In contrast, groundwater is often available in vast quantities and is usually sufficient to dampen-out seasonal variation of inflow. Groundwater reserves are usually orders of magnitude larger than surface storage. For example, in California the most productive and important aquifers consist of alluvial deposits in the Sacramento, San Joaquin and Tulare basins. In these regions 90% of groundwater use is for agriculture (DWR 1998, p3-49). In the San Joaquin River region 2.6 maf of groundwater is extracted in a 'typical' year. In the Tulare Lake region, 5.6 maf is extracted in a typical year. Central Valley usable groundwater storage capacity is estimated at 102 maf (DWR 1975, p58 & 65). For perspective, Lake Shasta, the State's largest reservoir, has a storage capacity of 4.5 maf and an annual average runoff at Shasta dam of 5.7 maf.

Water can be stored in aquifers either directly through active recharge or through in-lieu techniques. Active recharge is achieved by using either special percolation or injection facilities, supplementing flows to streams that seep to groundwater, or through excess irrigation. Artificial recharge methods are discussed by Bauman (1965), Todd (1980), Huisman and Olsthoorn (1983), and Oaksford (1985). In-lieu techniques involve the substitution of surface water for groundwater in wet years in areas that have traditionally relied on supplemental groundwater pumping. Surface supplies are subsequently foregone in periods of drought. In addition to system costs, several issues need to be addressed in considering an artificial recharge program for conjunctive use: loss of recharged water due to lateral movement out of the basin; opportunity cost of land required for recharge operation; presence of salts in recharge water; risk of waterlogging during the recharge period; risk of land subsidence, aquifer compaction, and water quality deterioration during drawdown; and third party impacts on pumping lifts.

Legal Aspects

The legal status of groundwater affects its use and management. "Groundwater" has no single legal meaning. Various categories are recognized by different state laws, including: percolating water; subterranean water; artesian water; tributary water; rechargeable water; channelized water; mineral water; and geothermal water (Bachman et al. 1997, p83). Although the inter-dependence of surface and groundwater water is now recognized, groundwater law has evolved under the premise that surface and groundwater are distinct entities. In many states attempts to create comprehensive legislation governing the use of groundwater has been unsuccessful. Groundwater management has remained the prerogative of local rather than state agencies.

The separate legal status of surface water and groundwater has hindered development of conjunctive use. USACE (1988) identify several legal questions that may affect the implementation of a conjunctive use scheme:

- What is the impact of artificial recharge on the water rights of landowners whose property overlies the recharge aquifer?

- How are appropriative and prescriptive rights to groundwater affected by artificial recharge?

- How will "rules" of conjunctive use water management be enforced?
- Who should take the loss of any increased basin outflow and how should this be determined?
- What is the legal liability of any damage due to changes in water table elevation, e.g. water logging, aquifer compaction and land subsidence?
- What is the legal liability with regard to changes in groundwater quality caused by artificial recharge?

. The legal aspects overshadow all other institutional planning considerations for conjunctive use (USACE 1988).

Institutional Setting

Falling water levels and deteriorating water quality have resulted in concern over how groundwater resources should be managed. Economists attribute the problems of groundwater to the current system of incomplete property rights (Bruggink 1992a). In general the property rights apply to the use of rather than the water itself. In the case of groundwater, ownership is initiated by withdrawal – the rule of capture. This combined with its common-pool characteristics and third-party effects has resulted in both technical and allocative inefficiency. Water scarcity is considered an allocation rather than a supply problem. Under the current institutional framework there is little incentive for owners of water rights to make provision for future use, invest in water saving technology or transfer/sell water to higher value uses.

Economic Aspects

The optimal economic allocation of groundwater is that which maximizes the net discounted benefits from the development and use of the resource while accounting for the negative externalities caused by excessive drawdown. Gross benefits as represented by consumer surplus can be determined by integration of the demand curve. An economic objective for groundwater extraction in a particular region (assuming no inter-region water transfers) may be formulated as:

$$\underset{Q_w^t}{Max}\, Z_{reg} = \sum_{t=1}^{n}\left(\frac{1}{1+\rho}\right)^t \left\{ \int^{Q_{reg}^t} D_{reg}\left(\sum_{w=1}^{W} Q_w^t\right) dQ - \sum_{w=1}^{W} C_p\left(Q_w^t, h_w^t\right) \right\} \qquad (1)$$

where D_{reg} is the aggregate demand for the region, Q_w^t is the groundwater pumped in period t from well w, C_p is the development and operational cost function for groundwater use which depends on the head and discharge at well w, and ρ is the discount rate over a n-period planning horizon. For conjunctive use operation equation (1) can be modified to include R surface water reservoirs:

$$\underset{Q_w^t, Q_s^t}{Max}\, Z_{reg} = \sum_{t=1}^{n} \left(\frac{1}{1+\rho} \right)^t \left\{ \int^{Q_{reg}^t} D_{reg} \left(\sum_{r=1}^{R} Q_s^t + \sum_{w=1}^{W} Q_w^t \right) dQ - \sum_{w=1}^{W} C_p \left(Q_w^t, h_w^t \right) - \sum_{r=1}^{R} C_s \left(Q_s^t, S_s^t \right) \right\} \quad (2)$$

where C_s is the development and operational cost function for surface water use, which depends on both the release and storage at reservoir r.

Operating Rules

Management of surface reservoirs typically is guided by formalized operating rules. These vary from simple release rules such as required when storage levels infringe on the flood control space or more complex rules that balance storage between reservoirs, determine delivery deficiencies in dry years and set carryover storage targets. A successful conjunctive use scheme requires definition of similar operating rules. Minimum and maximum acceptable groundwater levels need to be established. Trigger levels need to be set that initiate groundwater withdrawals during periods of low surface water availability. Rules governing groundwater recharge must be formulated.

Groundwater Management Models

Taxonomy

Van der Heijde et al. (1985) define groundwater management as the "planning, implementation and adaptive control of policies and progress related to the exploration, inventory, development and operation of water resources containing groundwater," Computer models have proved a very useful tool in guiding management decisions. Various classifications of groundwater models have been suggested (Bachman et al. 1980, Gorelick 1983). Following the classification described by Van der Heijde et al. (1985), mathematical models have three broad roles. Predictive models simulate the response of the system to stress. Resource management models integrate hydrologic prediction with explicit management decisions. Identification models determine the most likely value of input (aquifer) parameters (recent advances in groundwater modeling have tied aquifer parameter identification and management decisions into a single model, Yeh 1992). Groundwater models can be further classified according to their spatial aggregation (distributed parameter vs. lumped parameter) and according to the mathematical techniques employed to obtain a solution (simulation vs. optimization). Groundwater models may be limited in scope only representing aquifer response to external inputs or alternatively integrate surface and groundwater systems. In addition to flow, groundwater models may be concerned with mass transport and land subsidence.

Resource Management Models

In the last two decades many studies have coupled optimization models with physically based deterministic or stochastic groundwater simulation models to determine optimal strategies for meeting management objectives. Gorelick (1983) divides groundwater management models into two categories. Models that are principally concerned with managing flow, head and mass transport in the aquifer are termed "hydraulic management models". In contrast, "policy evaluation and allocation models" are concerned with economic efficiency and the influence of institutions, usually with respect to the agricultural sector. Hydraulic management models usually assume complete management control of the groundwater system. In contrast many policy evaluation and allocation models are concerned with influencing groundwater extraction using various economic instruments.

Lumped vs. Distributed Parameter

Lumped parameter models are mainly concerned with the temporal allocation of water. Distributed parameter models are required to answer questions of spatial and temporal allocations. Distributed parameter groundwater models are expensive and time consuming to construct and run and very data intensive. Lumped models may be preferable where there are time and budget constraints or where little data exists to support a distributed parameter model. Groundwater hydraulic management models necessitate a distributed parameter approach. Policy evaluation and allocation models may use either a distributed or lumped parameter representation of groundwater.

Lumped Parameter

Lumped parameter groundwater representations are commonly used in integrated water resources and empirical economic models. Groundwater is treated as single-cell or one-dimensional 'bath-tub' in which the piezometric surface is horizontal (infinite transmissivity). Lateral groundwater flow in and out of the basin is either ignored or pre-processed. Parameter values for the models are usually taken from more detailed distributed parameter simulation models. Provencher and Burt (1994a) present a good discussion on the validity of representing groundwater using single-cell or bathtub models. In reality, instead of groundwater quickly adjusting to a common depth, groundwater pumping causes a local zone of depression around the well. Equilibrating flows are driven by the hydraulic gradient. For a given transmissivity, the flow rate is proportional to the hydraulic gradient. Where equilibrating flows are slow due to low permeabilities, groundwater acts more like a private property. Provencher and Burt (1994a) regard the economic 'bath-tub' model as representing the worse case scenario.

Lumped parameter models usually discretize time into annual or monthly time steps. The equation of motion for these models can be written in terms of the total groundwater stock (X_t) at time t in the form:

$$X_{t+1} = X_t - W_t + \alpha Q_t + \beta I_t + R_t \qquad (1)$$

where W_t denotes groundwater withdrawals, Q_t is the surface streamflow, I_t denotes applied water, R_t is the natural recharge, α represents the fraction of stream flow lost to groundwater through deep percolation and β represents the fraction of applied water that percolates to the groundwater. For cases where β and R are zero, groundwater becomes a non-renewable resource. Where surface water supplies are stochastic in nature, it is usually assumed that groundwater extraction in each period takes place after the current surface water supplies have been realized (ex-post decision cf ex-ante). In the case of recharge there is an assumed lag between recharge and availability so that recharge during the current period is not available until the next period. Scarcity is often best understood in terms of water levels so that the equation of motion is often written in terms of piezometric head.

Typically lumped parameter groundwater models have been used to analyze the economic impacts of groundwater extraction on agricultural production. These vary considerably in sophistication. At the simplest level benefits are calculated as the area under a downward sloping demand curve for water. At the other extreme the farmer's production function is built into the model and the availability of groundwater and the cost of pumping influence crop mix and irrigation technology. Economic models are usually solved using linear, quadratic or stochastic dynamic programming techniques.

Distributed Parameter

Distributed parameter groundwater models are predominantly simulation models that solve the governing partial differential equations of groundwater flow using finite element or finite difference techniques (Pinder and Gray 1977, Prickett and Loungquist 1971, Trescott 1975). These types of models can represent groundwater wells, stream networks, recharge areas and other surface features. Simulation models have been used extensively to develop a better conceptual understanding of aquifer hydrogeology, and to study the system response to various management alternatives.

Groundwater simulation models may be coupled with optimization methods to directly solve for a management objective (Gorelick 1983, Ahlfeld and Heidari 1994). Two different approaches exist: the 'embedding' method and the 'response matrix' method (Gorelick 1983). In the first method the discretized groundwater flow equations are embedded within the optimization model forming part of the constraint set. This technique was first described by Aguado and Remson (1974). The decision variables are the heads and stresses such as pumping rates at each node and the boundary conditions. Subsequent examples of the embedded approach for water supply are described by Aguado et al. (1977), Willis and Newman (1977), Aguado and Remson (1980), Remson and Gorelick (1980), Willis and Liu (1984), Peralta et al. (1995). Many other papers describe the embedded approach with respect to management of groundwater contamination.

The response-matrix approach was first described in the petroleum engineering literature by Lee and Aronofsky (1958) and subsequently first applied to groundwater by Deninger (1970). The method is based on the principle of superposition of linear systems. The head at any node in the model can be expressed in terms of the initial head and the sum of unit responses to pumping at each well location during each time step. The groundwater simulation model is run independently of the optimization model to develop a set of fixed response equations or a response matrix that is incorporated as part of the LP constraint set. For unconfined aquifers, changes in the saturated thickness with pumping result in a nonlinear relationship between pumping and head. Reilly et al. (1987) showed that this could be ignored where changes in transmissivity are less than 10%, otherwise the nonlinearity requires an iterative solution procedure (Heidari 1982). Mixed integer programming combined with the response matrix approach has been used to determine optimal well locations. Examples of the response-matrix approach for water supply are Maddock (1972, 1974), Maddock and Haimes (1975), Morel-Seytoux and

Daly (1975), Morel-Seytoux et al. (1980), Heidari (1982), Illcongasekari and Morel-Seytoux (1982) and Willis (1984).

The embedding approach results in a very large constraint set with all the associated numerical solution difficulties. Until recently no large-scale application had been reported[13]. A large amount of output data is generated as the complete simulation model is solved for each time step. For management decisions this volume of data is rarely required. The embedded approach is therefore best suited for small or steady-state problems. In comparison, the response matrix approach yields less information about the response of the system but is usually much less computationally demanding: the response matrix being of smaller dimension than the discretized governing equations. For large steady-state problems involving many pumping cells, the embedded approach may be preferable.

Various authors have used time series models to approximate groundwater behavior (Law 1974, Houston 1983, Wanakule et al. 1986, Chagnon et al. 1988, Tankersley et al. 1993). Transfer functions can be used to relate the output behavior to past and present values of output and input series (Box and Jenkins 1976). They are generally applicable to systems that exhibit a dynamic response to one or more inputs. For example, Tankersley and Graham (1994) use a discrete transfer function optimal control scheme to reduce the expected deviation of piezometric head from monthly target levels. System response (piezometric head) was related to system inputs (rainfall and pumping). As for the response matrix approach, transfer functions result in a smaller optimization problem than explicitly modeling the governing equations.

Simulation vs. Optimization

Simulation models combine mathematical equations for physical processes with predefined rules for management decisions to determine step-by-step system operation for a deterministic sequence of inflow data. Through repetitive model runs the system response to various operating rules or strategies can be mapped. For conjunctive use these include put and take rules, extraction and recharge rates and groundwater storage capacities. Though simulation allows the physical system to be represented in greater detail than other mathematical techniques, determining optimal rules and management decisions is often a time-consuming trial and error affair. The important step of formulating a management objective function is often omitted so that modeling may proceed with little focus (Gorelick 1983) and does not guarantee an optimal solution as not all feasible strategies can be examined.

Optimization models use mathematical techniques to determine management decisions that maximize or minimize a stated, quantifiable objective subject to the physical governing equations and any imposed operational constraints. Objectives might be system yield, system reliability, or economic performance. For the majority of optimization models, optimal operating rules and required system (well) capacities must

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[13] Peralta et al.(1995) describe the use of the embedded method to maximize surface and groundwater yield for the Mississippi River Valley in NE Arkansas, a model of over 1,500 cells. A sequential steady-state modeling approach is used to account for the increase in demand with time.

be deduced from the prescribed system operation. To remain computationally tractable, optimization models must usually greatly simplify the system being modeled. They are therefore best applied as screening models of development alternatives prior to more detailed simulation.

The majority of conjunctive use optimization models reported in the literature use LP solvers. Integer LP maybe required for determining optimal well locations and representing well development costs. Application of classical DP to groundwater management problems is usually restricted to lumped parameter models. Distributed models require a large number of state variables (head at each node). To overcome this, Jones et al. (1987) present a differential DP algorithm for solving a large-scale, nonlinear optimization model.

Nonlinearities

Nonlinearities may arise due to the physical representation of the system or the assumed cost structure for surface and groundwater use. For unconfined aquifers the pumping-drawdown function is nonlinear. Stream-groundwater leakage can be represented by a linear function of stream stage and groundwater elevation where groundwater levels are at or above the streambed. Stage is a nonlinear function of discharge. Groundwater elevations depend on both stream leakage and recharge from irrigation. Groundwater pumping costs are nonlinear, being a function of the product of two variables: well drawdown and extraction rate. Hydropower revenues are similar a function of the product of the head across and the discharge through the turbines. Solutions to nonlinear models can be found using nonlinear solvers (e.g., Minos, Murtagh and Saunders 1977). Alternatively separable programming techniques may lead to solutions using quadratic programming or by LP using piecewise approximations of the resulting quadratic functions.

Stochastic vs. Deterministic

The vast majority of groundwater models are dynamic so as to account for: (a) the varying nature of surface water supplies, rainfall and recharge; and (b) the path through time of groundwater extraction either to a semi-steady state level or to resource depletion. The stochastic nature of hydrologic inputs is often represented implicitly using a deterministic time series based on historic flows (Labadie 1997). Alternatively rainfall, runoff and streamflow are treated as explicitly stochastic processes. The marginal distribution of flows may be assumed to be normal or log-normal distributed and modeled using a lag-one Markov model. Stochastic models may not be required in systems where the groundwater system dampens short-term variability in hydrologic inputs. Aquifer parameters uncertainty may also be modeled using stochastic optimization. Policy decisions in the face of uncertainty can be solved directly using stochastic dynamic programming. Alternatively, the predictions of the simulation models are represented as probabilistic functions of the decision variables. A Monte Carlo type analysis may be used to represent a series of realizations of uncertain parameters. Several studies have examined the effect of stochasticity on groundwater management. These include uncertainties of aquifer parameter and the random nature of surface and natural groundwater flows. Maddock (1974) found that results were sensitive to economic factors rather than aquifer parameters. A robust groundwater policy or management strategy is obtained by requiring the management model to simultaneously satisfy the constraints for multiple realizations of uncertain parameters. The presence of model uncertainty means that that any control strategy must be over-designed to ensure reliability while considering the trade-off between increasing system reliability and increasing cost (Wagner 1995).

Resource Management Model Applications

Hydraulic Management Models

Much of the current research addresses aquifer remediation design through the use of hydraulic management models. The focus is on local groundwater management and the control of head, flow and mass transport in isolation from the larger water resources system. Though not discussed here, new optimization techniques developed for these models may later be applied to regional rather than local water resources problems. Examples of hydraulic management models include: aquifer dewatering (Aguado and Remson 1974, Danskin and Freckleton 1992); maximizing safe yield (Deninger 1970, Larson et al. 1977, Heidari 1982); hydraulic gradient control for contaminant removal (Molz and Bell 1977, Remson and Gorelick 1980, Atwood and Gorelick 1985); water quality (Willis 1976, Gorelick and Remson 1982); aquifer restoration (Gorelick et al. 1984, Andricevic and Kitanidis 1990, Ahlfeld et al. 1995); and pollutant source management (Willis 1979, Gorelick et al. 1979). Wagner (1995) reviews recent advances in models for remediation design.

Policy-Institutional Models

Many regional conjunctive use studies are limited to the study of centrally controlled groundwater banks. However the majority of groundwater is usually extracted by private individual or firms responding to market forces. Economists have focused on developing theoretical models for the optimal extraction of groundwater over time. Acknowledging that the existing common property regime is economically inefficient, they have recommended various forms of groundwater management. Empirical models have been used to evaluate the efficiency of the proposed policy instruments.

<u>Common Property and Negative Externalities</u>

Groundwater is usually a limited open-access resource. Users share a common groundwater 'stock' with extraction generally limited to overlying landowners. Two externalities typically prevent the efficient use of the resource. The pumping cost externality is a function of the piezometric head; the stock externality exists where groundwater may be physically depleted. Historically economists have assumed that under the common property arrangement groundwater users execute myopic pumping decisions. Such behavior reflects the 'tragedy of the commons'. Alternative models have been suggested but Provencher and Burt (1994) report that from a survey of farmers in Kern County this model is a reasonable assumption. Where farmers pump from a common aquifer, an individual farmer cannot rely on future use of groundwater if he pumps less this year. Consequently instead of maximizing the present value of all future net benefits, farmers simply pump water each year until the marginal cost of pumping equals the value of the marginal physical product of water. Similar to other open-access resources, groundwater extraction is typified by over-use. Where aquifers are sufficiently deep they cannot be depleted economically and the stock externality can be ignored. Empirical economic models usually confine their analysis of the common property aspects of groundwater to the sharing of a common pumping lift and a common resource stock. Problems of water quality deterioration, land subsidence and permanent compaction of the aquifer are typically ignored. The cost of these effects is difficult to assess and are probably best treated by specifying a minimum water level below which extraction is prohibited.

Effect of Pumping Cost

Given that water demand can be significantly elastic in the price of water (Howitt et al, 1980), the cost of groundwater pumping can be a key factor in water use decisions. Caswell and Zilberman (1985, 1986) found that increased pumping costs can lead to the adoption of less water intensive irrigation technologies. Lichtenberg (1989) showed the converse, that reduction in the cost of pumping can shift farm production towards more water intensive cropping patterns. Shah et al. (1995) showed that under open-access there is insufficient adoption of conservation technology and the depletion of the groundwater stock is more rapid compared to the economic optimum.

Buffer Value of Groundwater

For many irrigated areas groundwater is a secondary, contingent supply that supplements surface water supplies in dry years. Surface water supplies, even when originating from large state or federal surface reservoirs, are typically stochastic in nature. The stock of groundwater therefore serves two purposes: to increase the overall supply of water and to dampen fluctuations in water supply to the farmer that would result in income variation. Tsur and Graham-Tomasi (1991) define the buffer value of groundwater to be the difference in the value of groundwater when conditions of uncertainty exist and its value where the surface water supply is stabilized at its mean. Using an empirical model for fossil groundwater extraction in the Negev (Israel) they show that the buffer value can exceed 50% of the value of the groundwater depending on the degree of surface water variability and the size of the groundwater stock

Artificial Recharge

The economics of active recharge depend on the variability of surface water supplies and the cost of groundwater pumping. Knapp and Olson (1995) determined optimal policies for Kern County, California. Using an SDP model, the authors show that it is profitable to store water at low head elevations, as there is insufficient stock to buffer the random surface water availability. At intermediate heads, there is sufficient stock to buffer surface water supplies but pumping costs remain high so that the marginal benefits from artificial recharge are low. At high elevations pumping costs are low and expected future withdrawals are large so that marginal benefits from recharge are again high. The shape of the demand curve also influences recharge. If the demand curve is elastic at low prices and inelastic at high prices this tends to increase recharge activity.

Central Control

The common property aspects of groundwater result in economic inefficiency. An important policy question is whether this justifies imposing external regulation. Imposed central control incurs significant implementation and monitoring costs. Various forms of central control are discussed by Burt (1970) and Gisser (1983). The problem for a central regulating agency is to restrict extraction so that the last unit of groundwater used in the current period is equal to the marginal value of the groundwater stock. The easiest form of control to implement is a pricing policy. A central authority sets the price for groundwater extraction equal to the marginal value of groundwater as a stock resource based on an economic model that calculates both the optimal price of water and the optimal path of extraction. The advantage of a pricing policy is that the marginal value of groundwater use is automatically equal for all farmers.

Gisser and Sanchez (1980) show that the economic benefits of the private property and central control regimes differ by a term $R/(rAS_y)$, where R is the natural recharge, r is the interest rate, A is the area of the aquifer, and S_y is the storativity or specific yield. Therefore, where the storage of the aquifer is large, the results under the two regimes are very close. Knapp and Olson (1995) found the annualized benefits from optimal regulated groundwater management in Kern County to be roughly $7 per acre per year compared to the common property, unregulated system. This low level of benefits is consistent with other results reported in the literature (Provencher and Burt 1994). The quasi steady-state optimal groundwater level under regulated control is generally higher than for the private property rights regime.

Tradable Groundwater Permits

Rather than rely on central management, many natural resource economists have advocated a system of well defined, exclusive and freely transferable property rights (Bruggink 1992b). Under a system of tradable permits the market rather than a regulator determine the path of resource use. A model for privatization is described in detail by Anderson et al. (1983). Private property rights are defined by a set of individual tradable permits that the owner controls over time. The right has two components: (a) a right to a percentage of the initial in-situ basin stock; and (b) a right to a percentage of the basin recharge. The system of permits provides an incentive for farmers to consider the effect of current decisions on future permit stock levels and income. Farmers can also reduce their total income variation by trading in groundwater permits (Provencher and Burt 1994b). As stock trade income and production income are negatively correlated the price of permits will increase in drought years so that the farmers stock trade income offsets loss in production income caused by water shortages. However the property rights regime is still not optimal as the pumping cost externality is still present.

Conjunctive Use Models

This section briefly reviews groundwater management models that have been reported in the literature for the conjunctive use of surface and ground water. The role of conjunctive use models is to identify the likely benefits of integrated operation of the groundwater surface water system. This may include system expansion (construction of new wells or surface water reservoirs) or simply the more efficient use (i.e. reduced reservoir spills) of existing facilities. At an initial planning stage lumped parameter simulation or optimization models may be sufficient to indicate promising alternatives. Much more detailed distributed parameter models are required to test the validity and impacts of any proposed scheme.

Lumped-Parameter Simulation Models

The usual focus of this class of model is the operation of the surface water system but with some limited representation of groundwater either for impact assessment on groundwater storage or for conjunctive use operations. Limited (single time step) optimization methods may be introduced to improve model flexibility.

The California Department of Water Resources simulation model DWRSIM provides a good example of this approach. The model was developed to study the operation of the California State Water Project and the federal Central Valley Project (Barnes and Chung 1986). Groundwater supplies are represented only implicitly in the model: the historic net contribution of groundwater in meeting consumptive demand is represented as a fixed inflow to the model. Additional groundwater pumping to meet projected level demands occurs only when surface water resources are exhausted. Projected groundwater use is preprocessed and similarly represented as fixed inflows and outflows representing periods of net groundwater extraction in the summer followed by recharge during the winter months. In the base model there is no dynamic operation of the groundwater resource nor is its availability reflected in the formulation of reservoir operating rules.

To model conjunctive use in DWRSIM, centrally controlled groundwater banks are represented as surface reservoirs with no losses. Groundwater banking operations are defined by imposed maximum storage, extraction and recharge rates and trigger levels for groundwater pumping and recharge. Many simulation runs are required to determine appropriate hedging rules defined by a delivery versus carryover storage risk-curve and corresponding trigger levels for groundwater withdrawals. Dvorak (2000) showed that the entire surface system must be re-operated to take advantage of the increase in groundwater storage flexibility.

Similar lumped parameter simulation models have been used by Jacquette (1978) to indicate the potential for re-operation of CVP reservoirs to explicitly account for groundwater, by NHI (1997) to investigate the feasibility of a groundwater banking program for California and by Andrews et al. (1992) to study conjunctive use operations in Kern County. Andrews et al. used network flow programming to determine the optimal allocations in each time step and so provide greater flexibility than prescribed linear operating policies.

Lumped-Parameter Optimization Models

Lumped parameter optimization models typically optimize operations over the entire period-of-analysis. Buras (1962) did some of the earliest conjunctive use studies involving a single surface reservoir and an aquifer supplying water for irrigation. DP was used to maximize expected returns given uncertain surface inflows. The DP model considered three state variables: surface water storage, groundwater storage and the volume of water available for active recharge.

Dracup (1966) used parametric linear programming to define an optimal conjunctive use program for the San Gabriel Valley in Southern California. Five different water sources were considered (local surface water, imported SWP water, imported Colorado River water, local groundwater, and reclaimed waste water). Cost coefficients, system capacities and demands were varied to investigate the robustness of the optimal policy. Trade-offs between multiple objectives were examined by changing cost coefficients.

Lefkoff and Kendall (1996) used a deterministic optimization model to evaluate yields from a ground-water storage facility operated in conjunction with the California State Water Project (SWP). The model maximizes long-term SWP yield over a 70-year period of reconstructed historic hydrology. The model includes nonlinear salinity-based regulatory standards that govern operations in the pivotal Sacramento-San Joaquin Delta. Groundwater storage is represented as a simple storage basin with constraints on maximum storage, extraction and recharge rates. The problem is solved using the Minos code of Murtagh and Saunders (1987).

Philbick and Kitanidis (1998) present a conjunctive use model for determining the least-cost operation of surface and ground water reservoirs given current storage and inflows. The problem is formulated as an SDP using an annual time step. Shortage and pumping costs are nonlinear. Annual streamflows are assumed to serially independent. The problem is solved using second-order gradient dynamic programming. The period-of-analysis is sufficiently long that the solution converges to steady-state.

Coupled Simulation – Optimization Management Models

Complex groundwater management decisions require groundwater to be represented at a level of detail afforded only by simulation models. Often this requirement has led to the development of separate groundwater simulation and surface water optimization models. The models either exchange data at time steps determined by the needs of the surface model, usually monthly or annually, or the response characteristics of the groundwater model are incorporated into the surface water model using the response matrix approach. The early applications of simulation-optimization models were restricted to stream-aquifer systems with the exchange of data between separate surface and ground water models rather than integrating the two. Some of the earliest applications are described by Thomas and Burden (1965) and Chun et al. (1972). Young and Bredehoeft (1972) developed a coupled groundwater-surface water model to study conjunctive use schemes in the South Platte Valley in Colorado. The surface water model included a LP agricultural production model. For a given streamflow and policy the surface model determined a set of monthly diversions and groundwater pumping that maximize revenues from irrigation subject to stream outflow requirements and predetermined well capacities. Each time step the groundwater model was run to determine aquifer recharge from irrigation and groundwater stream accretions. These become fixed inputs for the next time step of the surface water model.

More recently Danskin and Freckleton (1992) analyzed the problem of high groundwater levels in the San Bernardino Valley, California caused by a decrease in agricultural pumping. Linear programming was coupled with a transient pseudo three-dimensional aquifer model to determine the most efficient pumping policy. Lall and Lin (1991) developed a management model for Salt lake Valley, Utah. The objective is to minimize the annual cost of groundwater supply subject to drawdown, water rights and water quality restrictions.

Lall (1995) used a hybrid simulation-optimization approach for planning surface storage and groundwater development on the Jordan River, Utah. A reservoir yield model was used to identify the required reservoir capacity as a function of firm yield. A unit response matrix describing changes in head with pumping was developed from a separate groundwater simulation model. These model outputs were combined into a least-cost optimization model for resource development. The nonlinear optimization problem was solved using penalty successive linear programming (PSLP). Lall notes that conjunctive use of groundwater leads to "quite different 'optimal' reservoir sizes and well capacities." Lall's approach uses a deterministic reservoir yield model based on the critical period. A standard linear operating policy is followed with no consideration of hedging.

Belaineh et al. (1999) present a water resources management model that explicitly accounts for conjunctive use of groundwater in determining optimal reservoir operating rules. The model represents a reservoir-stream-aquifer system that supplies a collection of separate irrigated areas. Groundwater response to recharge and pumping is calculated using the response matrix approach. Matrix coefficients are determined from a separate three-dimensional groundwater simulation model. The authors determine parameters for S- and S-Q type linear decision rules that maximize water supply from surface and groundwater sources subject to various management constraints. The model is solved using linear programming. This approach has the advantage of a detailed representation of groundwater (though it is restricted to confined aquifers or unconfined aquifers of sufficient depth). Economic values for water use and cost of groundwater pumping could easily replace the existing objective of yield maximization. The main drawback is the use of monthly linear decision rules that result in an over-simplistic reservoir operation.

Basagaoglu et al. (1999) present a nonlinear simulation-optimization model to determine optimal policies for a reservoir-stream-aquifer system that supplies an agricultural region. A goal-programming approach is used to define a mixed objective of minimizing operating costs and minimizing weighted deviations from predefined reservoir storage targets. The nonlinearity due to the pumping cost is solved using separable programming and piecewise linear approximations of the resulting quadratic functions. Monthly demands are fixed rather than a function of the cost of water, so that the resulting operating policies may not be optimal under drought conditions. Penalties or weights for deviation from target storage are arbitrarily fixed and do not represent the relative benefits of storage versus releases. Basagaoglu et al. (1999) extend the concept of rule curves that have been used for surface reservoir operations (e.g., Vasiliadis and Karamouz 1994) to stream storage. It could similarly be extended to groundwater to maintain levels within an environmentally sound range.

Conclusions

Traditionally surface water management and groundwater development have been have been treated in separate and distinct planning studies, with few attempts to integrate the operation of both resources at a regional scale. This has been perhaps exacerbated by the separation within the engineering profession of groundwater modelers and surface water planners. Where regional planning studies have integrated models of both surface water and groundwater resources into a single model, there has been considerable simplification of either one or other element. Either groundwater has been represented by a lumped parameter model or over-simplified operating rules and inflow hydrology have been assumed for the surface system. Alternatively separate models have been developed for each resource and attempts to link the two have been frustrated by incompatibilities between the models.

Simulation models require that system operating rules be predefined. Coupled surface water groundwater simulation models require rules for reservoir releases and groundwater pumping. For complex systems, searches for 'optimal' conjunctive use rules are likely to be extremely time consuming. Optimization models can provide a tool for suggesting promising conjunctive use operations and aid in the formulation of operating rules prior to their testing in more detailed simulation models. Performance measures for rules should account not only for improvement in supply reliability, but groundwater development costs, head-dependent pumping costs and any long-term mining of the groundwater resource. .

Groundwater is too often considered a purely local resource. The use of conjunctive use optimization models can demonstrate the economic benefits from explicitly operating the surface water system to account for the availability of groundwater. Though lumped-parameter groundwater models are sufficient to indicate the potential benefits, more detailed distributed models are required to determine the feasibility and quantify the impacts of conjunctive use. The response-matrix approach allows greater detail to be included in an optimization model so allowing more sophisticated groundwater goals and constraints to be included.

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7. RESERVOIR OPERATION WITH CONJUNCTIVE USE OF GROUNDWATER

Introduction

Coordinated surface and ground water operating rules can improve supply reliability and water-use efficiency within a river basin. Increased groundwater extraction during dry years can offset reduction in stream flows. Conversely, in wet years, preferential use of surface water and active groundwater recharge can diminish reservoir spills and increase the ability of surface reservoirs to capture winter runoff. However, groundwater resources are often ignored in the formulation of reservoir rule curves and operating rules. The objective of this chapter is to develop a simple conjunctive use model to examine economic costs and benefits of integrated management of these two resources. Particular attention is drawn to decision-making under uncertainty, the impact of integrated operations on reservoir carryover storage, the development of optimal operating policies, and the effects of conjunctive use on modeling with perfect, imperfect, and myopic hydrologic foresight.

This chapter extends the work of Chapter 4, integrating groundwater into an implicitly stochastic reservoir optimization model. The model is applied in a simple case study of an irrigated system supplied from a single reservoir but with access to groundwater as a contingent supply. System operation is formulated as a deterministic network flow programming (NFP) problem. Model results are a set of prescribed monthly operations that minimize total costs over a 73-year time horizon that includes prolonged periods of both high and low flows. Some general conclusions are drawn on the influence of groundwater on optimal surface reservoir operation.

Previous Studies

Chapter 6 reviews conjunctive use operations, groundwater management models and their application to the development of optimal operating policies. Formal derivation of such policies is a stochastic control problem given the random nature of streamflows. Groundwater storage is usually sufficient to dampen impacts of variable groundwater recharge components from natural sources. Explicitly stochastic conjunctive use management models have been used to derive efficient control policies for both reservoir releases and groundwater extraction using SDP (e.g., Philbrick and Kitanidis 1998). However thy require the use of advanced mathematical techniques, such as second-order gradient DP (Philbrick 1996) and are limited to relatively simple systems with few state variables. Most explicitly stochastic models treat surface supplies as exogenous (whether unregulated streamflows or regulated reservoir releases) and exclude direct consideration of surface reservoir operation (e.g., Onta et al. 19991, Knapp and Olson 1995, Reichard 1995). The majority of models that do address both surface reservoir and groundwater basin operation are implicitly stochastic and prescribe optimal operations for a deterministic time series of inflows (Lall 1995, Lefkoff and Kendall 1996, Basagaoglu et al. 1999, Belaineh et al.1999). However, these models use simplified forms of reservoir operating rules, either linear decision rules (Basagaoglu and Marino 1999, Basagaoglu et al. 1999, Belaineh et al.1999) or standard release rules such as the standard linear operating policy (Lall 1995).

This chapter presents a conjunctive use management model that optimizes joint reservoir groundwater basin based on a deterministic time series of reservoir inflows but, in contrast to previous work, accounts for risk in the prescribed release decisions. Though the approach is demonstrated using a single reservoir and a lumped-parameter representation of groundwater it can be extended to multi-reservoir systems and more detailed groundwater representation using response equations.

New Approach

Management Model

The adopted model is that described in Chapter 4, except that groundwater is now included as an additional storage node in the network configuration (see Figure 7.1). Additional links represent groundwater pumping and deep percolation from irrigation. All other recharge to groundwater (e.g., from lateral groundwater movement or percolation of precipitation) is preprocessed and represented as an external flow to the groundwater node. The lumped parameter representation of groundwater is sufficient to demonstrate the impact of groundwater availability on optimal reservoir operation. Linear penalties on pumping represent variable operating (energy and maintenance) costs. Optimal release and pumping policies are determined using HEC-PRM, a network flow optimization code (USACE 1994a). The objective function is expressed as cost minimization, as described in Chapter 2.

As discussed in Chapter 4, the model may be run in three modes: perfect foresight; limited foresight; and myopic operation. When operations are optimized for a time horizon equal to the period-of-analysis, the model is omniscient, sometimes leading to unrealistic storage operations. In the limited foresight mode, the model is run sequentially using 12-month time spans. Initial storage in one run is set equal to the ending storage of the preceding run. Penalty functions attached to carryover storage are used to limit drawdown in any particular run and reflect the expected value of storage given the stochastic nature of future inflows. Myopic operation corresponds to the standard linear operating rule (SLOP).

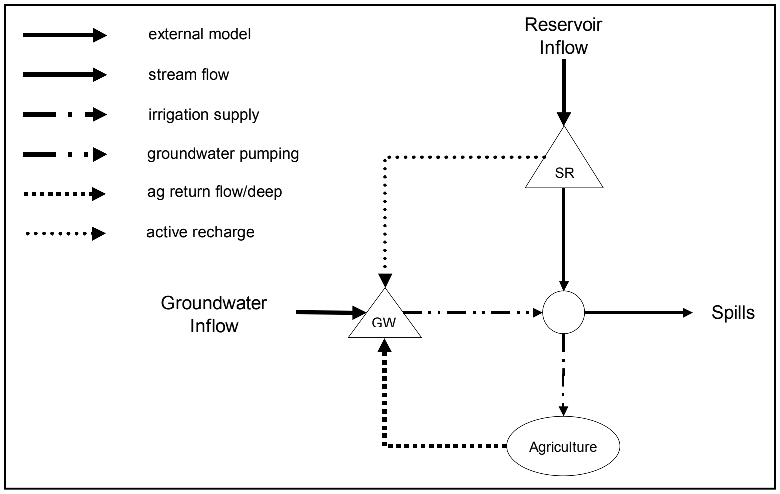


Figure 7.1 Node-Link Diagram for Surface Reservoir-Groundwater System

Benefits from perfect foresight accrue in a stochastic setting when reservoir inflows are highly variable and when the refill potential of the reservoir is significantly less than one. The impact of perfect foresight is curtailed by reservoir spills in wet years that reset the system. At very low or very high storage to inflow ratios, the influence of perfect foresight becomes unimportant (see Chapter 4). In contrast to surface reservoirs, many aquifers have extremely large unused storage volumes, whose access comes at some pumping cost. For many agricultural areas groundwater storage acts as a contingent supply, buffering the variation in surface supplies. Though the effect of perfect foresight becomes less important, some type of operating rule is needed to prevent over-extraction and mining of groundwater resources. Simple rules for groundwater extraction can be developed based on the average combined yield of the surface-groundwater system compared to demand.

Model Assumptions and Limitations

The conjunctive use model has been simplified to avoid non-linearities associated with the real physical system. Groundwater pumping costs reflect the marginal cost of pumping and exclude capital and depreciation costs. Unit pumping costs are held constant (i.e., head independent). Stream-groundwater interaction that is a function of stream stage and groundwater elevation is ignored. No costs are attributed to surface water supplies. The conveyance channels are assumed to be a gravity system. Operation and maintenance costs are assumed to be independent of surface deliveries and are not included.

A consequence of using a network flow model is that any groundwater recharge is available in the same time-step. Although physically unrealistic, it is not a serious limitation unless groundwater nears some minimum storage threshold.

Only aggregate groundwater storage can be represented using a lumped parameter model. A response matrix approach would allow management goals, beyond forbidding groundwater mining, to be modeled as head and flow constraints.

The model currently does not account for hydropower revenues. Optimal carryover storage levels partially depend on the value of hydropower. Reduced carryover storage results in a lower head across the turbines. This is offset by a reduction in spills; so greater flow through the turbines. Conjunctive use of groundwater could affect hydropower revenues in two ways. Firstly through the timing of releases, surface releases would be made in months of high electricity demand and groundwater pumping in months when the cost of electricity is lower. Second and more importantly, greater groundwater banking as an alternative to surface carryover storage would reduce the head across the turbines, decreasing the power generated from a unit release. Incorporation of these hydropower aspects is not beyond the general approach presented here.

The proposed model is not suited to the problem of capacity expansion and the determination of the optimal level of groundwater development. Integer Linear Programming (ILP) models would permit well installation and replacement to be represented as a one-time cost incurred if groundwater withdrawal exceeds a threshold value anytime during the period-of-analysis. Using a network flow program, identification of the optimal installed well capacity requires an iterative process (e.g., a grid search). Results could be post-processed to include well installation and replacement costs based on maximum pumping rates. Alternatively the pumping capacity constraint can be successively raised until at the optimal installed capacity the expected value of the Lagrange multiplier on the capacity constraint will equal the marginal cost of well installation and replacement.

Case Study

Description

Consider an extension of the one reservoir problem for Lake McClure described in the last chapter. The agricultural region now has access to local groundwater. The cost of pumping is represented by a fixed unit cost on the groundwater pumping link. Non-consumptive use of the irrigation supply returns to the groundwater system as deep percolation. Irrigation water 'lost' through evapotranspiration is represented by a gain factor of less than one on the agricultural return flow link (any return flow to the stream network is also lost to the system so that for this example it can be represented implicitly as part of the gain factor). A set of piecewise linear monthly economic penalties are attached to the delivery link to the agricultural region to represent the cost of water shortage. Monthly upper bound constraints on the irrigation supply preclude delivery of water in excess of demand for the purpose of active recharge. As in Chapter 4, the surface reservoir is constrained by a constant lower bound (minimum operating level) and a monthly varying upper bound (flood control/reservoir capacity). Initially groundwater is unconstrained; storage is considered infinite with no constraints on terminal storage. Inflows to the reservoir are the reconstructed October 1921 – September 1994 historic unimpaired monthly flows. The average annual inflow is 914 taf/yr. Average groundwater inflow is arbitrarily set at 100 taf/yr with an initial (arbitrary) storage of 10 maf. Annual agricultural demand for water at zero economic loss is 605 taf/yr, with no inter-annual variation of demand. Pumping costs are held constant at $30/af. Demand at this level of cost is 581 taf/yr. Four scenarios are examined: (1) no access to groundwater; (2) independent reservoir and groundwater operation; (3) in-lieu conjunctive reservoir and groundwater operation; and (4) active recharge of groundwater.

Scenario 1: No Access to Groundwater

From results presented in Chapter 4 for Lake McClure, optimal management under perfect foresight in the absence of groundwater results in an average annual yield of 587 taf/yr and a corresponding average annual shortage of 18 taf/yr. The average annual cost of shortage is $1.23 million/yr. In 14% of months the willingness-to-pay for water exceeds the $30/af cost of groundwater pumping. Under limited foresight the average annual yield drops slightly to 578 taf/yr; the shortage rises to 27 taf/yr. Average annual shortage costs rise to $1.94 million/yr. The willingness-to-pay for water exceeds the cost of pumping in 30% of months. Average annual yield and shortages under myopic operation are as for perfect foresight but the average annual cost of shortage is $2.62 million/yr. In only 9% of months does the willingness-to-pay for additional water exceed the cost of groundwater pumping. The SLOP results in the lowest total number of months of shortage, but these include months of extreme shortage. In contrast perfect foresight attenuates these peaks by spreading the shortage over a longer period.

Scenario 2: Independent Reservoir and Groundwater Operation

Under Scenario 2 the surface reservoir and groundwater are operated independently or “disjunctively”. The scenario represents an agricultural region where some areas are supplied from surface water, while other areas rely solely on groundwater. No agricultural area has access to both resources. As the area dependent on groundwater is increased, the proportion of demand met by surface water diminishes so increasing its supply reliability. The purpose of Scenario 2 is to provide base costs for comparison with conjunctive use operation under Scenario 3. It is implemented by constraining groundwater pumping to a fixed monthly pattern so that the annual extraction equals the product of the percentage area supplied by groundwater and the demand at a price of $30/af. Figure 7.2 shows shortage costs as a function of the area dependent on groundwater for the three cases of perfect foresight, limited foresight and myopic operation. The reduction in shortage costs at the expense of increasing groundwater costs is similar in the three cases. Shortage costs are negligible beyond an area of 25% dependent on groundwater. Perhaps surprisingly, total costs rise monotonically with no minimum being observed[14]. For the limited foresight runs, the value of carryover storage was re-optimized for the varying levels of exclusive groundwater supply. If the value of carryover storage is held constant, the reduction in shortage cost with groundwater access is less pronounced. The high value of carryover storage induces high-levels of hedging that are unwarranted for the increased reliability of surface supplies.

[14] The occurrence of a minimum depends on the average cost of shortage compared to the cost of groundwater pumping. If 1% of the area is supplied by groundwater, the annual cost of groundwater pumping is $174,000 plus an annual shortage cost for the area of $3,250. Under limited foresight with no access to groundwater there are 38 years of shortage with an average willingness-to-pay of $55/af. In these years approximately 5,550af would become available due to a 1% reduction in the area leading to an annual average cost reduction of $160,000.

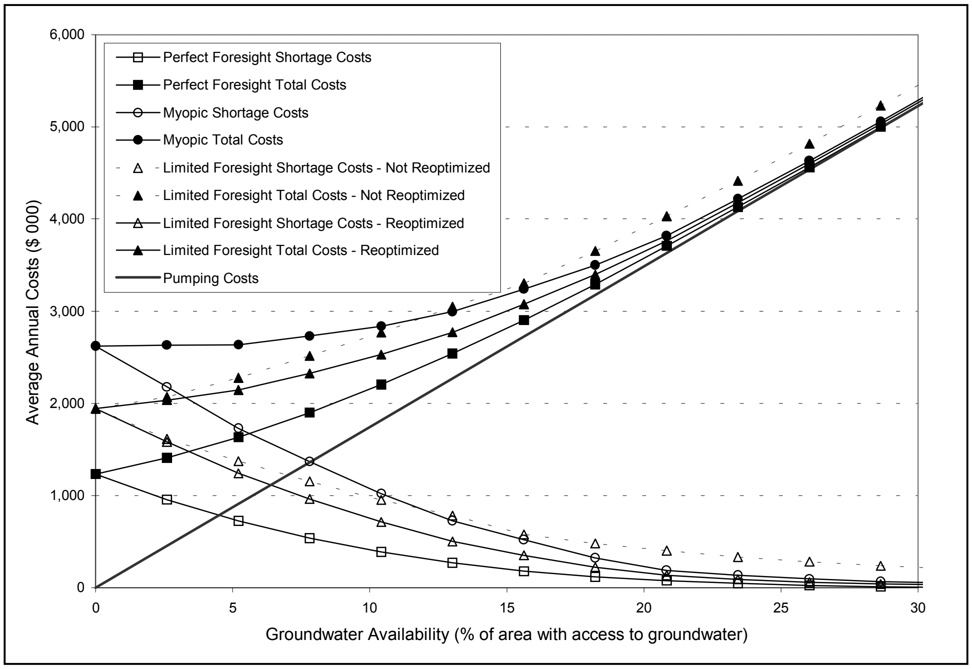


Figure 7.2 Average Annual Costs as a Function of Exclusive Groundwater Supply

Scenario 3: In-lieu Conjunctive Reservoir and Groundwater Operation

In-lieu conjunctive use of groundwater is represented under Scenario 3. Under this scenario it is assumed that all of the area can be supplied with surface water. Two limiting cases on groundwater extraction are considered: (a) the upper bound on monthly pumping is limited to a fixed fraction of full demand representing the situation where only some of the area has access to supplemental groundwater; and (b) monthly pumping is unconstrained but total pumping over the period-of-analysis is constrained to avoid long-term mining of the groundwater resource. For both cases there are no lower bound groundwater pumping constraints.

(a) Upper Bounds on Monthly Pumping

The ability to practice conjunctive use increases with the fraction of the agricultural region that has access to groundwater. Groundwater supplements supplies in dry years, so directly reducing shortage costs. Secondly, it partially eliminates the need to hedge against drought conditions, increasing average year surface deliveries, reducing reservoir spills, and increasing the ability of the reservoir to capture winter runoff. Figure 7.3 shows the effect of groundwater availability on cost. Under perfect foresight (Figure 7.3a) average annual costs fall to a constant value of 464 taf/yr beyond 30% access to groundwater. This reduction in cost is due entirely to the provision of additional water rather than any changes in hedging policies. Hedging under perfect foresight is always optimized and so does not affect the ability of the reservoir to capture winter runoff. Under myopic operation (Figure 7.3b) average annual costs similarly fall, reaching a constant value of 496 taf/yr. Similarly to perfect foresight this drop is due to the additional groundwater yield rather than its insurance value. The small difference in total costs between the myopic and perfect foresight models at high groundwater availability is due to the avoidance of pumping costs due to hedging under perfect foresight.

The most interesting changes are observed for costs under limited foresight (Figure 7.3c). Initially the value of carryover storage is set equal to that determined for Scenario 1, i.e., optimal for no groundwater supply. As access to groundwater is increased this implied reservoir operating rule becomes far from optimal. Initially total costs fall. However beyond 18% groundwater availability, total costs start to rise and reach a constant value of $1,812 taf/yr at 80% groundwater availability; a cost far in excess of both perfect foresight and myopic operation. The surprising increase in costs is explained by the high assigned value of carryover storage. During drought years when the reservoir would otherwise be drawn down at the end of the water year, the model pumps additional water to not only supplement but replace surface deliveries so by increasing carryover storage and reducing the ending storage penalty. This behavior not only results in additional pumping costs but also increases reservoir spills by maintaining unnecessarily high levels of carryover storage.

To better quantify the cost of not reformulating reservoir operating rules, the limited foresight model was re-run with carryover storage fixed at the optimum Scenario 1 levels. These were compared to costs incurred for revised optimal carryover storage value functions that explicit account for the existence of groundwater. The resulting costs for the fixed and reoptimized formulations are shown in Figure 7.3c. These were compared with the costs incurred when reservoir operation was fixed. As expected, explicitly adjusting reservoir operation to account for groundwater results in substantial benefits. The adjusted limited foresight model performs better than myopic operation but less well than under perfect foresight. As potential groundwater supplies increase, the value of carryover storage falls, reflecting its decreased ‘insurance’ value (Figure 7.4). Table 7.1 below gives the reductions in shortage costs achieved through conjunctive rather than independent operation. The savings are significant.

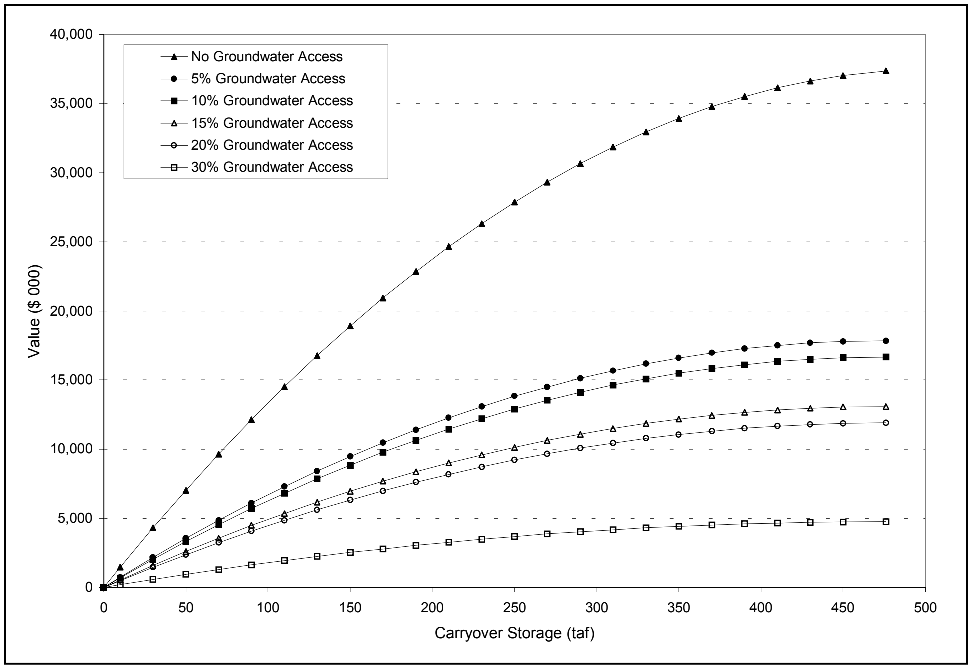


Figure 7.4 Effect of Groundwater Pumping on the Value of Carryover Storage under Limited Foresight

Table 7.1 Comparison of Average Annual Total Costs under Independent and Conjunctive Management of Surface and Ground Water Resources

Time Horizon	Independent Operation ($ 000)		Conjunctive Operation ($ 000)		Reduction in Costs (%)	
	10% GW	20% GW	10% GW	20% GW	10% GW	20% GW
Perfect Foresight	2,202	3,707	659	494	70	87
Limited Foresight[1]	2,477	3,781	1,081	832	56	78
Myopic Operation	2,838	3,818	1,813	1,292	36	66
Notes: 1. For re-optimized carryover storage penalty function						

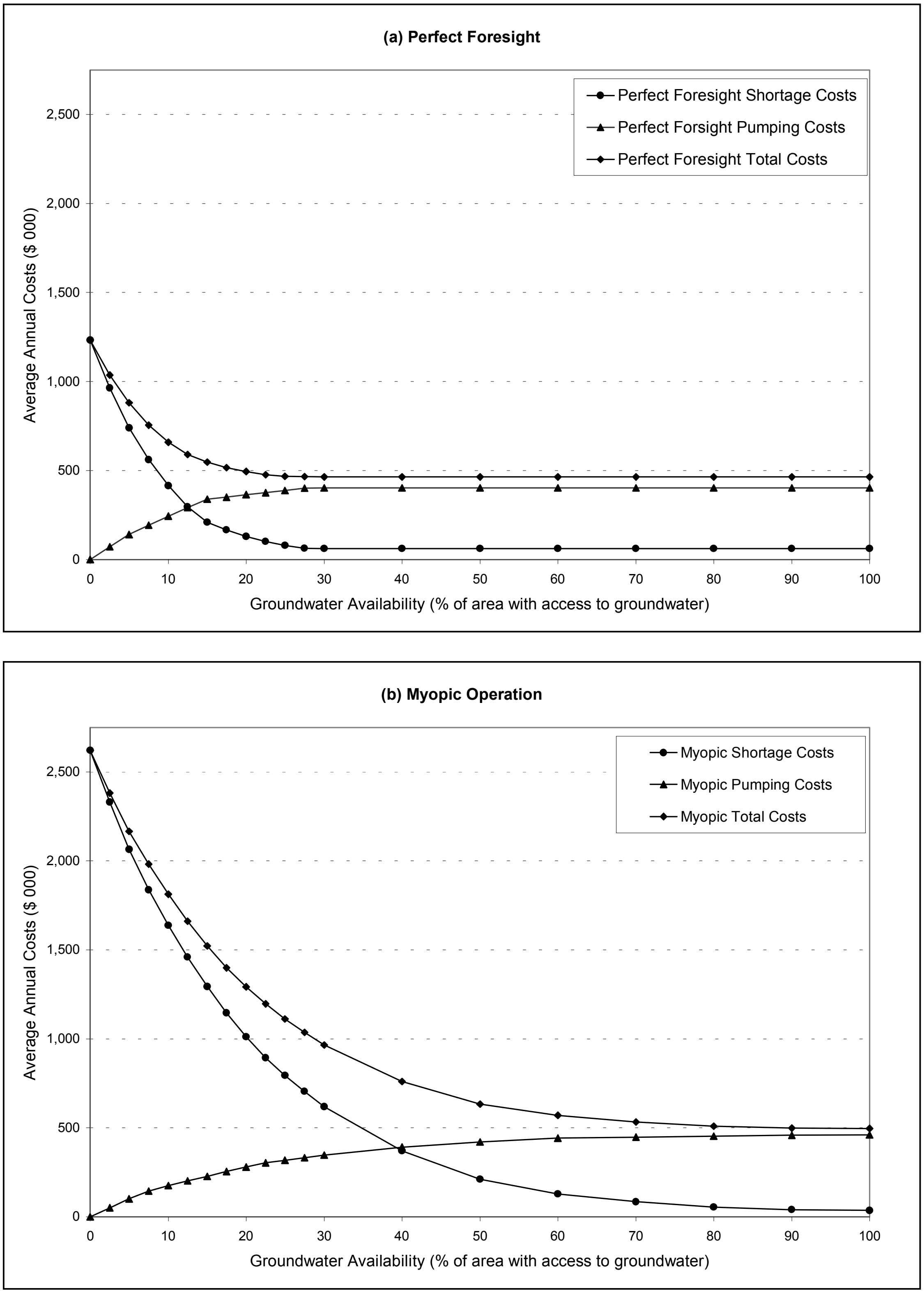
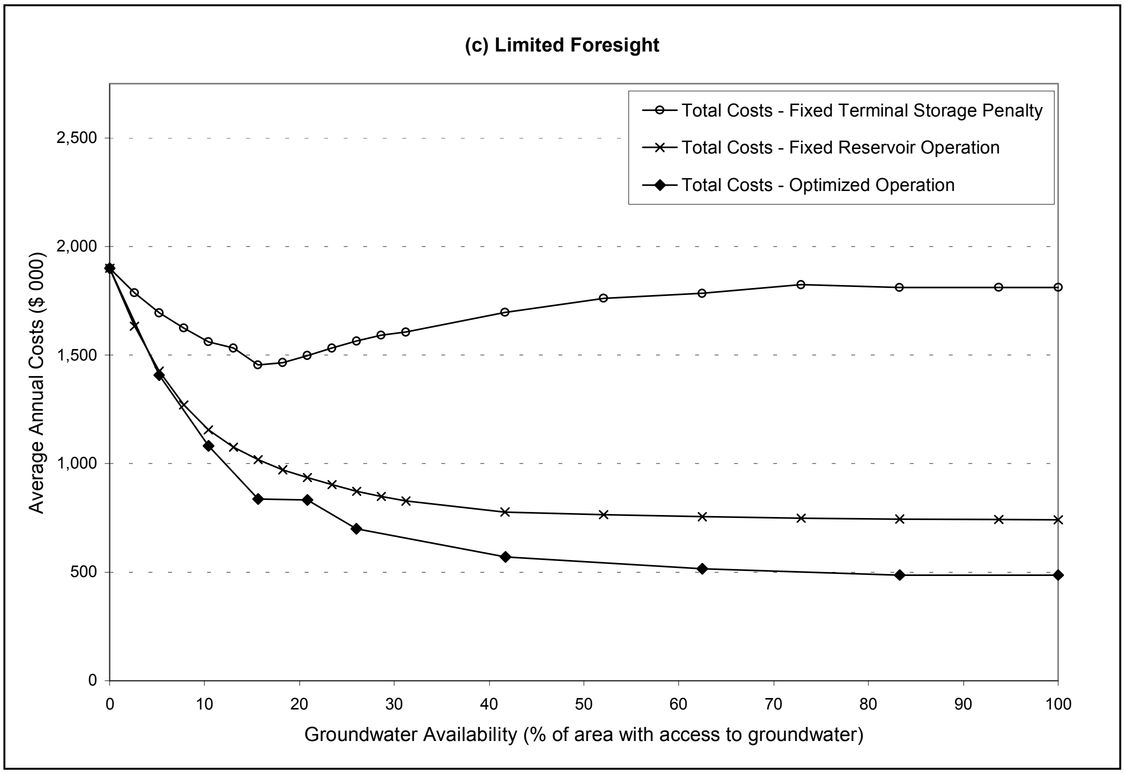


Figure 7.3 Average Annual Costs under Perfect Foresight, Limited Foresight and Myopic Operation



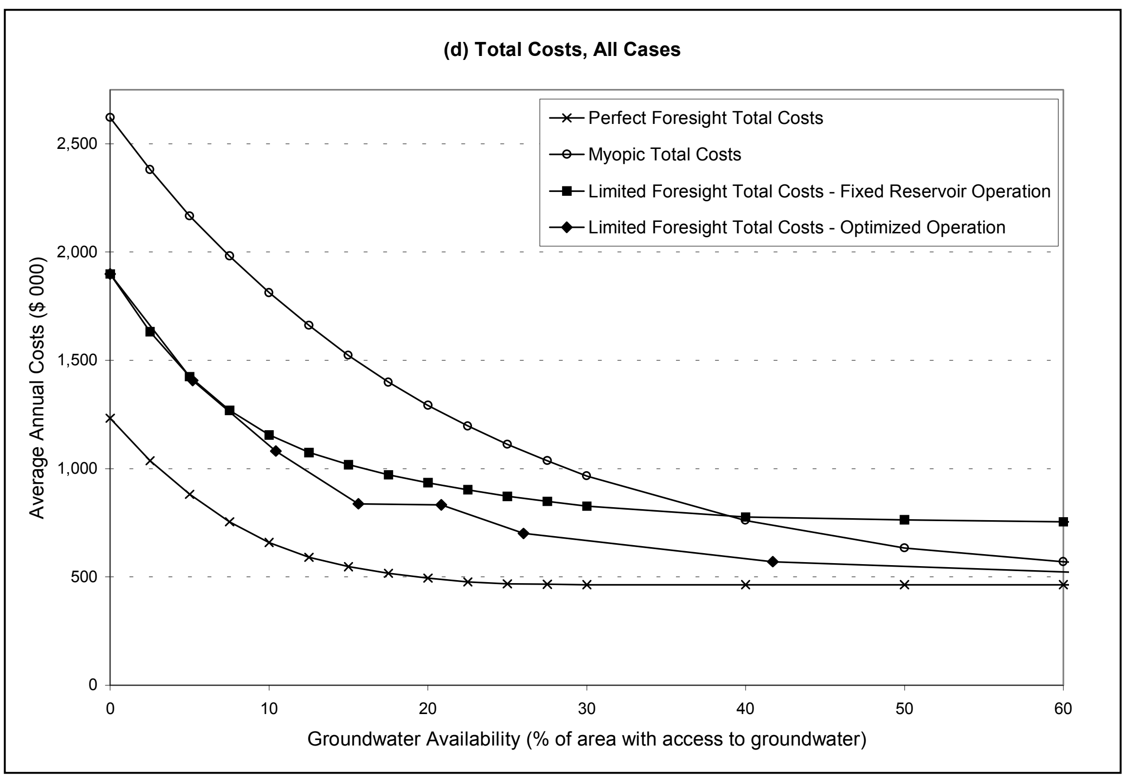


Figure 7.3 Cont…

(b) Constraints on Groundwater Mining

It is assumed that over a sufficiently long period-of-analysis there should be no net groundwater depletion. Groundwater mining often is undesirable due its unsustainable nature and possible negative impacts of land subsidence, aquifer compaction, deteriorating water quality, saline intrusion, and reduced stream base flow. A ‘no groundwater mining’ constraint can be readily enforced for the case of perfect foresight by setting terminal storage equal to initial storage. The resulting shadow value on terminal storage will equal the unit value of groundwater mining. Extending the inflow time series forwards and backwards using average hydrologic conditions can remove the influence of the initial and ending conditions. The problem is to find a method to enforce the no groundwater mining constraint for the limited foresight model. In the absence of this constraint, groundwater will be extracted at every time step until the marginal value of water (slope of the monthly penalty function on the delivery link) equals the cost of pumping. Although groundwater storage is unlikely to become exhausted and there is no equivalence to the risk of spills, the concept of carryover storage cam be extended to the groundwater systems. The no groundwater mining constraint can be achieved by applying a penalty the ending groundwater storage of each 12-month run[15].

Under the Lake McClure model described so far groundwater use is modest, with an annual average of 14 taf/yr under limited foresight when access to groundwater is unrestricted. To better demonstrate the effect of groundwater scarcity, and the implementation of the no groundwater mining constraint, agricultural demand is increased by an arbitrary factor of two. The groundwater external inflow is set to zero. Deep percolation from irrigation is set to 15% of applied water so that under full deliveries groundwater recharge would total 181 taf/yr. It is assumed that 100% of the agricultural region now has access to groundwater.

Management Under Perfect Foresight

Consider the optimal schedule of reservoir releases and groundwater pumping prescribed under perfect foresight. Without groundwater constraints the model will extract groundwater until the marginal cost of shortage falls below the cost of groundwater pumping. Given the relative magnitudes of reservoir inflows and demands, this would result in a groundwater overdraft (at zero pumping cost) of approximately 442 taf/yr. (average annual reservoir inflow = 914 taf/yr, average annual spill = 327 taf/yr, average surface delivery = 587 taf/yr, annual demand = 1210 taf/yr). If groundwater mining is prevented by constraining terminal storage to the initial storage, groundwater supplies become scarce, so pumping will occur only in months of maximum shortage. For a continuous penalty function, the volumes pumped will equalize the marginal cost of shortage across the months of pumping. Given the piecewise linear nature of the agricultural penalty function, this is somewhat approximate. Figure 7.5 shows the monthly marginal cost of shortage for the 73-year period. Months depicted in black

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15 Though not considered in this chapter, it could alternatively be achieved by increasing the cost of pumping.

represent months of groundwater extraction. Groundwater pumping reduces the maximum marginal cost of shortage to $153/af. In months of no groundwater use the marginal cost is always less[16]. Figure 7.6 shows monthly storage levels over the 73-year period. The beginning and ending storage is 10 maf. After the six-year 1928-34 drought, all groundwater operations are driven by the anticipated 1987-92 drought. With a few exceptions, groundwater pumping is curtailed to maximize groundwater storage prior to this drought period. Although the extraction pattern is obviously determined by perfect foresight, a similar pattern would be followed by a central groundwater authority that knew only average groundwater basin and reservoir yields over the 73-year period, refraining from groundwater use except during severe droughts. Figure 7.6 shows that the limited foresight model gives almost the same groundwater storage results, except that it is a little slower to recognize the onset of drought.

Interpretation of Marginal Costs and Lagrange Multipliers

The marginal cost of shortage is reported by HEC-PRM as "Dual_Origin" values on the irrigation supply link. These indicate the value (cost) of increasing (decreasing) the upstream node's fixed external flow by one unit (USACE 1999). The cost of one less unit of groundwater supply, the Dual_Origin on the groundwater pumping link, are constant for all months over the period-of-analysis (except the last month where an additional unit of supply is only available for the month following the end of the period-of-analysis). The shadow value on the EOP groundwater storage constraint is reported by HEC-PRM as "Marg_Cost_S". It equals the cost (benefit) of increasing the lower (upper) bound on EOP storage by one unit. The monthly values are zero except for the

[16] Care must be taken interpreting the marginal costs of shortage and willingness-to-pay. Irrigation deliveries often occur up to a breakpoint in the agricultural penalty function. Under such conditions the steeper slope to the left of the breakpoint determines the marginal value of pumped groundwater. Values to the right reflect the marginal value of additional groundwater pumping.

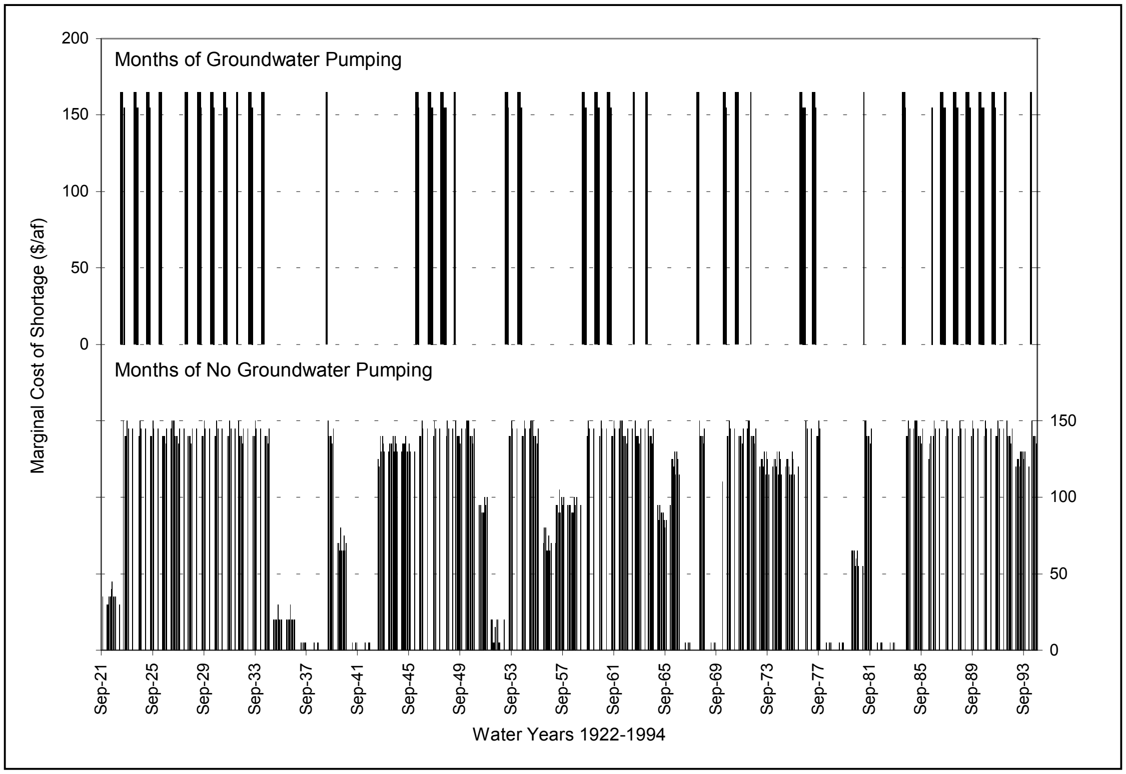

Figure 7.5 Groundwater Pumping and the Marginal Cost of Shortage

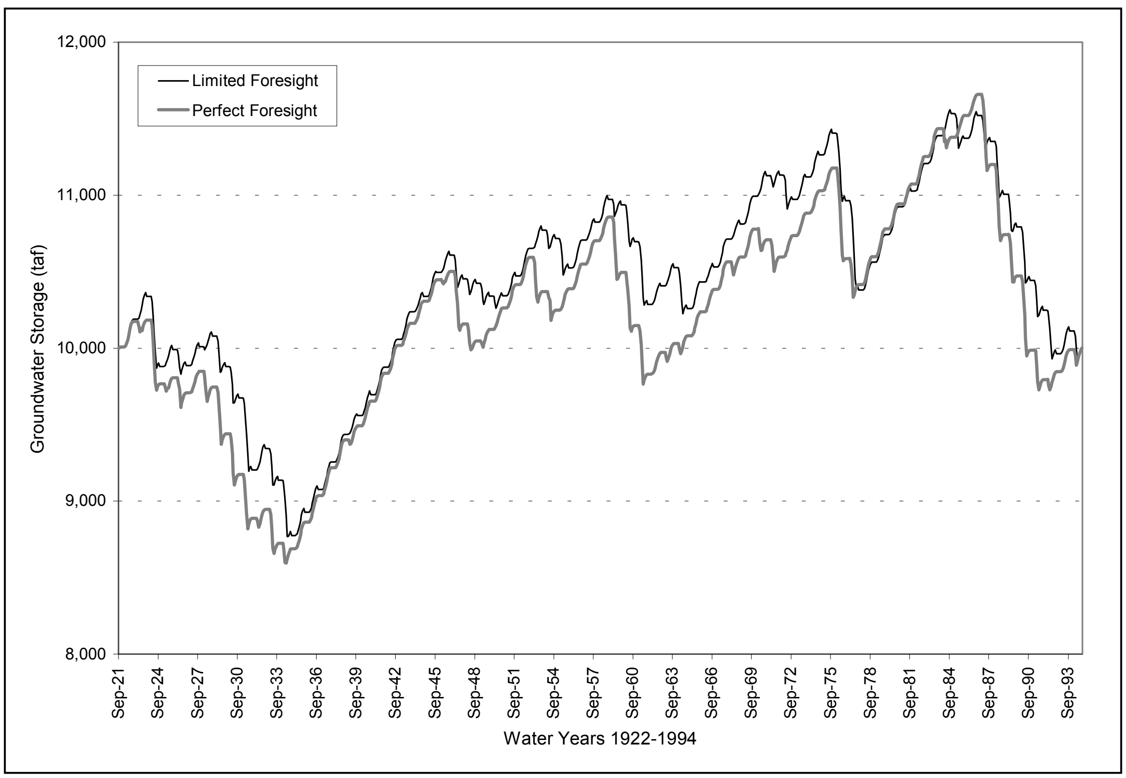

Figure 7.6 Groundwater Storage under a "No Groundwater Mining" Constraint

terminal month when the Marg_Cost_S value equals the Dual_Origin on the groundwater pumping link.

For systems other than this very simple case study, the calculation of the value of groundwater mining is complex. One additional unit of groundwater results in ever decreasing volumes of deep percolation being re-used for irrigation. The Dual_Origin on the groundwater pumping link is \$144.67/af. The cost of pumping is \$30/af. The fraction of reuse is 0.15. Farmers' maximum marginal willingness-to-pay (slope of the delivery penalty function at the monthly delivery) is \$152.94/af, which occurs in 25 of the months, then falls to a slightly lower value. The value of an additional unit of groundwater (or unit relaxation of the mining constraint) is therefore approximately:

$$(152.94-30)\sum_{i=0}^{25} 0.15^{i}$$

$$(152.94-30)+0.15(\cdot)+0.15^{2}(\cdot)+......0.15^{25}(\cdot)$$

$$\approx 122.94*\frac{1}{1-0.15} \quad \text{as } 0.15^{25}\rightarrow 0$$

$$=144.64$$

Management Under Limited Foresight

Carryover storage penalties on groundwater storage are required to run HEC-PRM with limited foresight. Initially the carryover storage penalty is set equal to the shadow value on the terminal storage constraint determined from the perfect foresight run. If shortage costs under limited foresight are similar to perfect foresight no mining would occur. However operations under perfect foresight are more efficient so that the value of groundwater is underestimated. Pumping under limited foresight using carryover storage penalties equal to the marginal cost of shortage from the perfect foresight run will therefore result in some groundwater mining. This can be overcome by incrementally raising the carryover storage penalty until no groundwater mining occurs. Table 7.2 gives a comparison of shortage and operating costs for the perfect and limited foresight models obtained using this approach. A comparison of groundwater storage operations are shown in Figure 7.6

Table 7.2 Average Annual Costs under the No Groundwater Mining Constraint

	Carryover Penalty (\$/af)	Shortage Costs (\$ 000)	Pumping Costs (\$ 000)	Total Costs (\$ 000)
Perfect Foresight	145	15,113	4,499	19,612
Limited Foresight	205	19,729	4,497	24,226
Note For limited foresight reservoir operations have been reoptimized				

Effect of Pumping Constraints

To investigate the effect of pump capacity constraints on groundwater operations upper and lower bounds were imposed on monthly groundwater pumping. Upper bounds on pumping represent either limits imposed by the installed pump capacity or areas that do not have access to groundwater. Lower bounds reflect areas reliant on groundwater, without access to surface water. The minimum pumping rate was fixed at 10% of monthly demand. The maximum pumping rate was set at 125% of the largest minimum monthly pumping rate. The results appear in Figure 7.7. The difference in groundwater operations indicate the importance of accurate representation of groundwater capacities and constraints are required if groundwater storage operations are to be accurately modeled. As pumping operations increasingly constrained, there is likely to be less room for perfect foresight to affect operations.

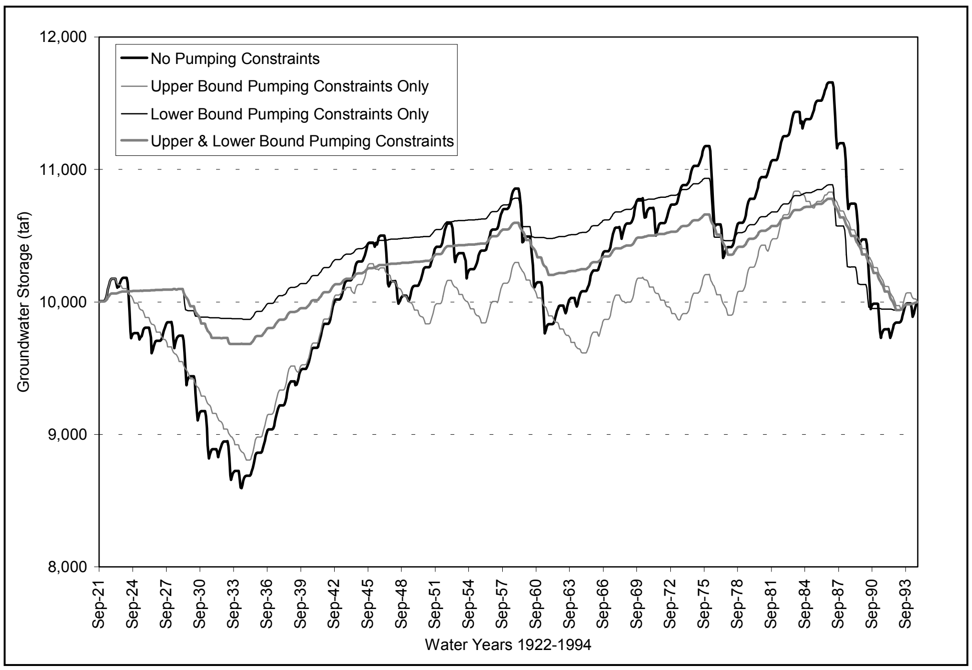

Figure 7.7 Effect of Groundwater Pumping Constraints on Groundwater Storage

Scenario 4: Conjunctive Reservoir and Groundwater Operation with Active Recharge

An active recharge program involves the deliberate percolation of surface water into an aquifer system for later retrieval and use. The hypothetical system represented in Figure 7.8 is similar to that described by Buras (1963, 1972) and Yakowitz (1982). Active recharge is modeled using a separate groundwater basin (labeled GW1) so that benefits accruing from groundwater banking can be separated from those accruing from pumping of natural recharge and previously applied irrigation water. As for the previous scenarios, extraction costs are set at $30/af. Recharge costs depend on the characteristics of the site and the recharge method employed. In addition to operation and maintenance of the recharge facility variable costs may include those associated with the upstream distribution system, prior water treatment and the opportunity cost of land. For the current model, a constant marginal cost of $25/af has been assumed. There is no upper bound on capacity and it is assumed there are no losses associated with the active recharge program. Maximum agricultural demand is set at 605 taf/yr as for Scenarios 1 and 2. Annual demand for water at a cost of $55/af is 557 taf/yr, or 48 taf/yr less than the maximum demand. To focus on the recharge activities, pumping of natural recharge and previously applied irrigation water from basin GW2 is set to zero. Surface reservoir spills are extremely large, averaging 325 taf/yr.

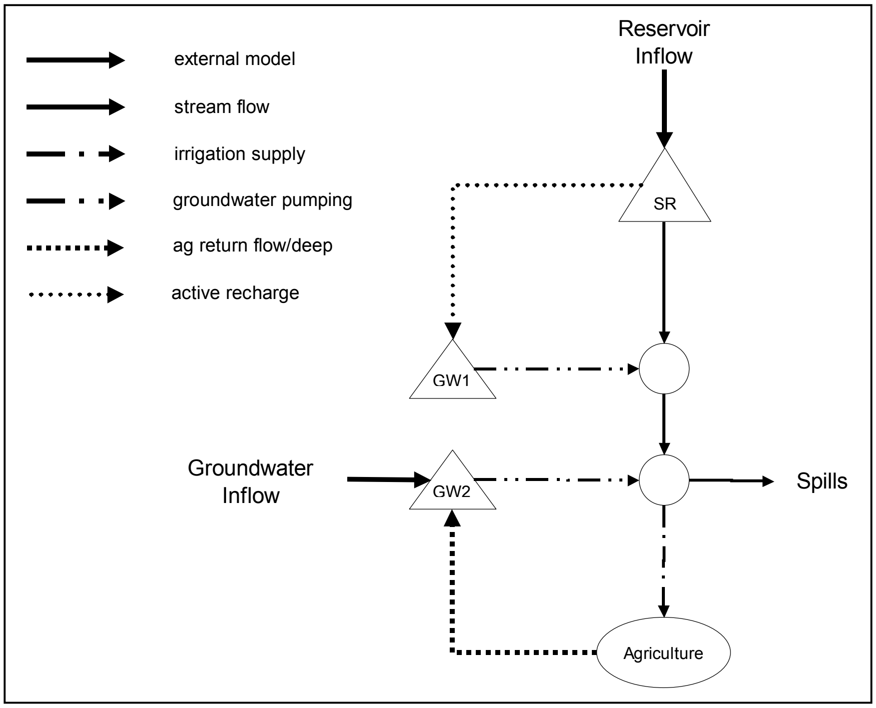

Figure 7.8 Node-Link Diagram for Surface Reservoir-Aquifer System with Active Recharge

Table 7.3 summarizes the mechanics of representing an active recharge program in the perfect foresight, limited foresight and myopic models using a mix of constraints and penalties.

Table 7.3 Implementation of Active Recharge for Optimization over Varying Time Horizons

	Perfect Foresight		Limited Foresight		Myopic Operation
	Preferential Use of Surface Water	Preferential Use of Groundwater	Fixed Operations	Optimized Carryover Storage Penalty	
(a) Constraints					
End-of-period SW storage	none	none	none	none	none
End-of-period GW storage	= initial storage[5]	= initial storage[5]	none	none	none
SW storage	monthly varying upper bound	monthly varying upper bound	constrained time series	monthly varying upper bound	monthly varying upper bound
	constant lower bound	constant lower bound	constant lower bound	constant lower bound	constant lower bound
GW storage	constant upper bound = initial storage[2]	constant upper bound = initial storage[2]	none	none	none
Agricultural deliveries	monthly varying upper bound[4]	monthly varying upper bound[4]	monthly varying upper bound[4]	monthly varying upper bound[4]	monthly varying upper bound[4]
(b) Penalties					
Carryover penalty on SW storage	varies $0-$30/af[1]	varies $0-$30/af[1]	none	varies $0-$30/af[1]	none
Monthly penalty on agricultural deliveries	varies $7/af-$720/af	varies $7/af-$720/af	varies $7/af-$720/af	varies $7/af-$720/af	Varies $7/af-$720/af
Monthly penalty SW storage drawdown below top of conservation pool	$0.02/af	$0.02/af	none	$0.03/af	$0.03/af
Monthly penalty GW storage drawdown below initial level	$0.03/af	$0.01/af	$0.02/af	$0.03/af	$0.03/af
Active recharge	$25.00/af	$25.00/af	$0.01/af	$0.02/af	$0.02/af
Groundwater pumping	$30.00/af	$30.00/af	$55.00/af	$55.00/af	$55.00/af
Penalty on stream outflow	$0.01/af[3]	$0.01/af[3]	none	$0.01/af[3]	$0.01/af[3]

Notes:
1 Storage penalty for perfect foresight for 09/93 as for limited foresight to achieve similar ending conditions
2 Ensures groundwater basin is recharged after rather than prior to periods of extraction
3 Ensures water held in storage rather than spilled in last month of run where model otherwise indifferent
4 Prevents over irrigation for purpose of active recharge
5 Prevents groundwater mining

<u>Perfect Foresight</u>

Under perfect foresight groundwater mining is prevented by setting the final storage for GW1 equal to the initial storage. Groundwater banking results are summarized in Table 7.4. In the absence of groundwater, shortages for Scenario 1 under perfect foresight are 18 taf/yr resulting in an average cost of $1.23 million/yr. The introduction of the active recharge link results in an average of 10 taf/yr being banked for later use. Annual average deliveries for irrigation increase to 597 taf/yr. Shortages fall to 8 taf/yr, shortage costs fall to $214/yr. Active recharge and pumping costs are $529/yr giving a total cost of $743/yr. Groundwater banking reduces the maximum marginal cost of shortage in years of deficit surface water supplies to $55/af.

Table 7.4 Average Annual Impact of Groundwater Banking

Time Horizon	Vol. Banked	Vol. Pumped	Shortage	Pumping & recharge Costs	Shortage Costs	Total Costs
	(taf)	(taf/yr)	(taf/yr)	($000/yr)	($000/yr)	($000/yr)
No GW Banking						
Perfect Foresight	0	0	18	0	1,230	1,230
Groundwater Banking						
Perfect Foresight	10	10	8	529	214	743
Limited Foresight - Fixed Operations	12	13	18	696	429	1,125
Limited Foresight - Optimized	11	12	9	638	138	776
Myopic	13	13	5	695	145	840

Figure 7.9 compares reservoir operation under perfect foresight with (Scenario 4) and without (Scenario 1) groundwater banking. For most years reservoir storage and releases are unaffected by the active recharge program as only reservoir spills are banked. Only during the 1987-1992 drought do reservoir operations between Scenarios 1 and 4 diverge. For this period under Scenario 1 carryover storage is gradually drawn down until in 1992 it reaches the minimum operating level so as to equalize shortages across years. Under Scenario 4, initial shortages are met from groundwater and only subsequently is carryover storage drawn down. A more realistic operation would be to preferentially use surface water in the first year of drought and to subsequently switch to groundwater if and when drought conditions continue. This preferential use of surface water can be implemented through a monthly persuasion penalty on groundwater that penalizes deviations from a target storage level. The persuasion penalty on groundwater storage must be set above that used on surface storage (e.g. 0.03 compared to 0.02 $/af).

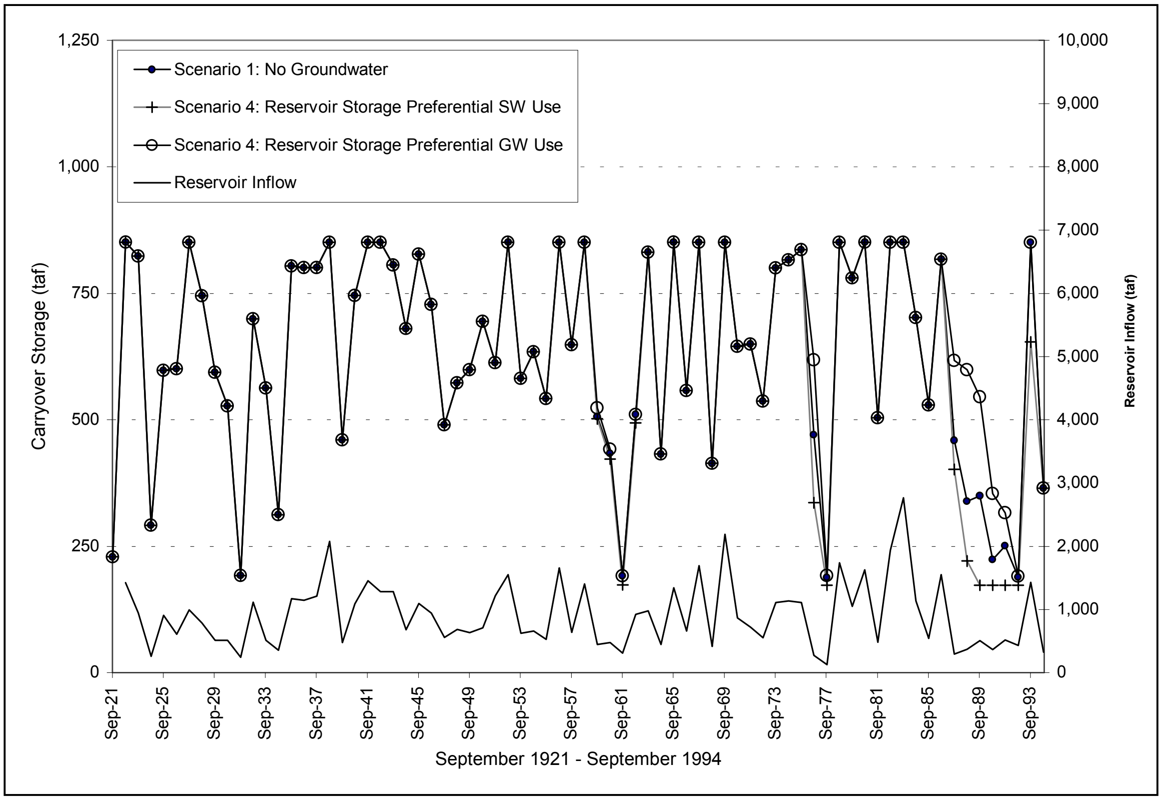

Figure 7.9 Reservoir Operation with and without Groundwater Banking under Perfect Foresight

Myopic Operations

Myopic operation is discussed before the limited foresight model as the results better demonstrate the distortions due to perfect foresight and the need for hedging even though groundwater banking insures against extreme shortages. Under myopic operation, groundwater banking of surface water can be encouraged by extending the concept of rule curves developed for surface storage. Active recharge of spilled water can be implemented using a linear penalty on annual carryover storage set slightly above the recharge cost, i.e. $25.01/af. The storage volume that equates to zero penalty should be chosen so that there is always adequate storage in dry years to meet demand. For the case study the point of zero penalty is the initial groundwater storage so that in wet years following a drought groundwater is recharged up to its initial level. Under myopic operation subsequent extraction of groundwater storage would occur until the willingness-to-pay falls below $30/af. Given the recharge cost, the optimal cut-off point for extraction is at a willingness-to-pay of $55/af. This difficulty can be overcome by adjusting the recharge cost for the myopic model to $0.02/af, setting the carryover storage penalty to $0.03/af , and the pumping cost to $55/af. The persuasion penalty on surface water storage is set equal to $0.03/af so that only excess water will be used for active recharge[17]. The persuasion penalty on groundwater storage is less than that used

[17] Care must be exercised in the sizing of persuasion penalties. A penalty of $0.01/af on storage can generate significant additional costs if changes in operation result in changes in storage over an extended time, e.g. 1af of additional storage over a six-year drought is equivalent to $0.72.

for surface storage so that whenever possible surplus water is held in the reservoir rather than banked. The persuasion penalty on recharge ensures excess water is spilled rather than used for artificial recharge once groundwater storage is at its initial value.

Results for myopic operation are summarized in Table 7.4. With no groundwater, shortages under myopic operation occur in 12 years averaging 18 taf/yr. Groundwater banking reduces the average annual shortage to 13 taf/yr. Average annual costs at $840,000/yr are only 13% higher than those achieved under perfect foresight. Myopic operation results in larger volumes of groundwater banking and lower shortages (the SLOP rule will always minimize the expected value of shortages). These are offset by the costs of recharge and pumping.

Under drought conditions when groundwater pumping is initiated the marginal value of water is $55/af. In years when surface water is not limiting, the marginal value of water drops to zero. However economic benefits are maximized when the marginal value of water is equalized across all months in all years of the period-of-analysis. Under perfect foresight this is prevented by constraints on surface storage. Under the SLOP it also prevented by the inherent lack of foresight.

However, perfect foresight uses optimal hedging to spread shortage costs, when they occur, over a longer period. In the year(s) prior to a prolonged drought, water is retained in storage rather than meeting current deliveries. The opportunity cost of deliveries foregone is of the order of 10 $/af. During an extreme drought years this surface water is substituted for groundwater pumping that has a cost of $55/af. Average annual shortages under perfect foresight are slightly higher due to hedging. By spreading shortages over a greater time span, shortages under mild droughts may fall below the critical level of 48 taf/yr that initiates groundwater pumping. As only the timing rather than the volume of surface supplies changes, the reduction in pumping under perfect foresight during mild drought events causes greater shortages. Figure 7.10 illustrates the differences in myopic and perfect foresight operation immediately prior to and during the extreme 1987-1992 six-year drought.

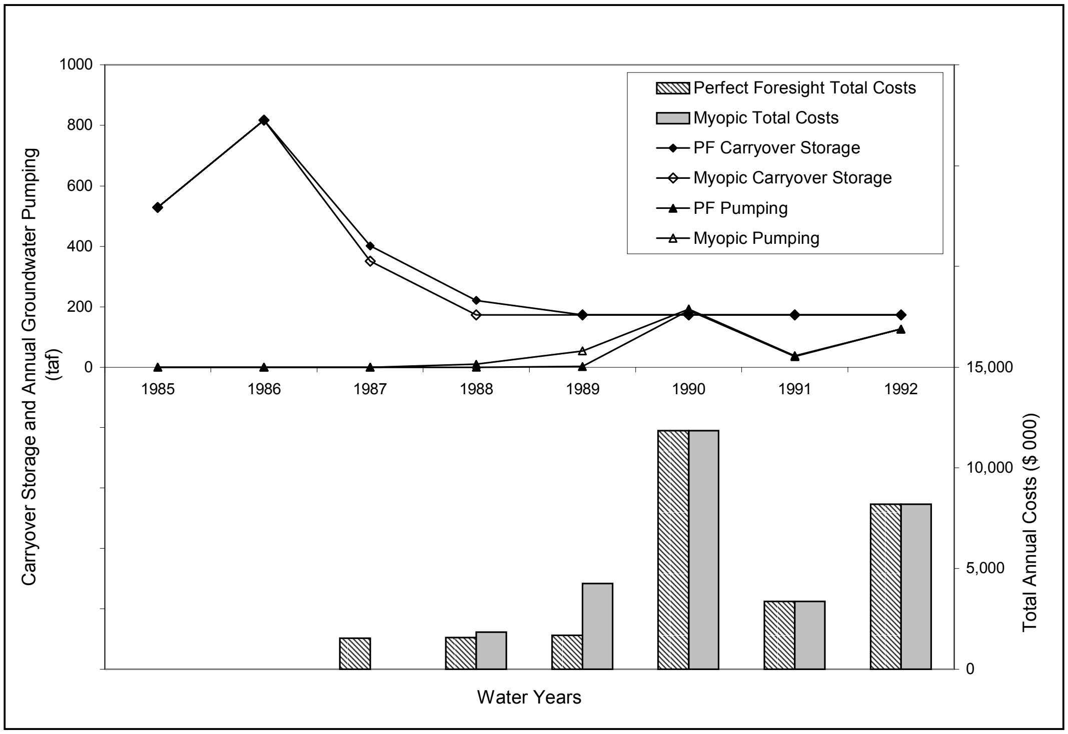

Figure 7.10 Reservoir Storage under Groundwater Banking 1985-1992 under Perfect Foresight and Myopic Operation

<u>Limited Foresight</u>

Initially the limited foresight model is run enforcing the carryover storage volumes established for Scenario 1. The model is then rerun to establish new carryover storage penalties that are optimal for conjunctive use operations. Results are given in Table 7.4. The observed small differences in the annual average pumping and the average annual water banked is due to the period-of-analysis ending soon after a prolonged drought. Not adjusting carryover storage operations for the presence of groundwater results in a significant cost: costs under optimized operations are 69% of the fixed operations costs or $349 million/yr less. Shortage and shortage costs for the optimized limited foresight model are very close to those achieved under perfect foresight. In general the presence of large groundwater storage negates the effects of perfect foresight so that model runs under limited and perfect foresight tend to converge to a similar operating policy. This similarity of reservoir operations under perfect and limited foresight are shown by Figures 7.11 and 7.12. The observed differences under drought conditions are due to the difference in costs of surface and groundwater. The relative costs of surface water and groundwater assigned in this example are arbitrary. For municipal utilities use of groundwater may be preferable due to its lower treatment costs.

Summary and Conclusions

Conjunctive use of surface and ground water requires the development of operating rules that explicitly account for the availability of groundwater storage. Reservoirs characterized by a high coefficient of variation of annual inflows ($C_v > 1$), and a low standardized net inflow ($m < C_v$) are typically operated for over-year storage[18]. The transfer of carryover storage from the surface to the groundwater system reduces the risk of spills and increases the ability of the surface water system to capture winter runoff. This is off-set by an increase in pumping costs. Identification of 'optimal' release policies or rules for complex systems requires the use of systems analysis. Deterministic models can be relatively easily constructed and solved using network flow programming, a restricted form of LP. These models, however, prescribe optimal system operation for a single set of inflows using perfect foresight. Considerable time and expertise are subsequently required to tease-out general operating rules based only on the operator's current and past knowledge of the system (USACE 1994b)

[18] The standardized net inflow or m index was introduced by Hazen (1914) and is defined as the mean annual inflow less the average yield divided by the standard deviation of the annual inflow.

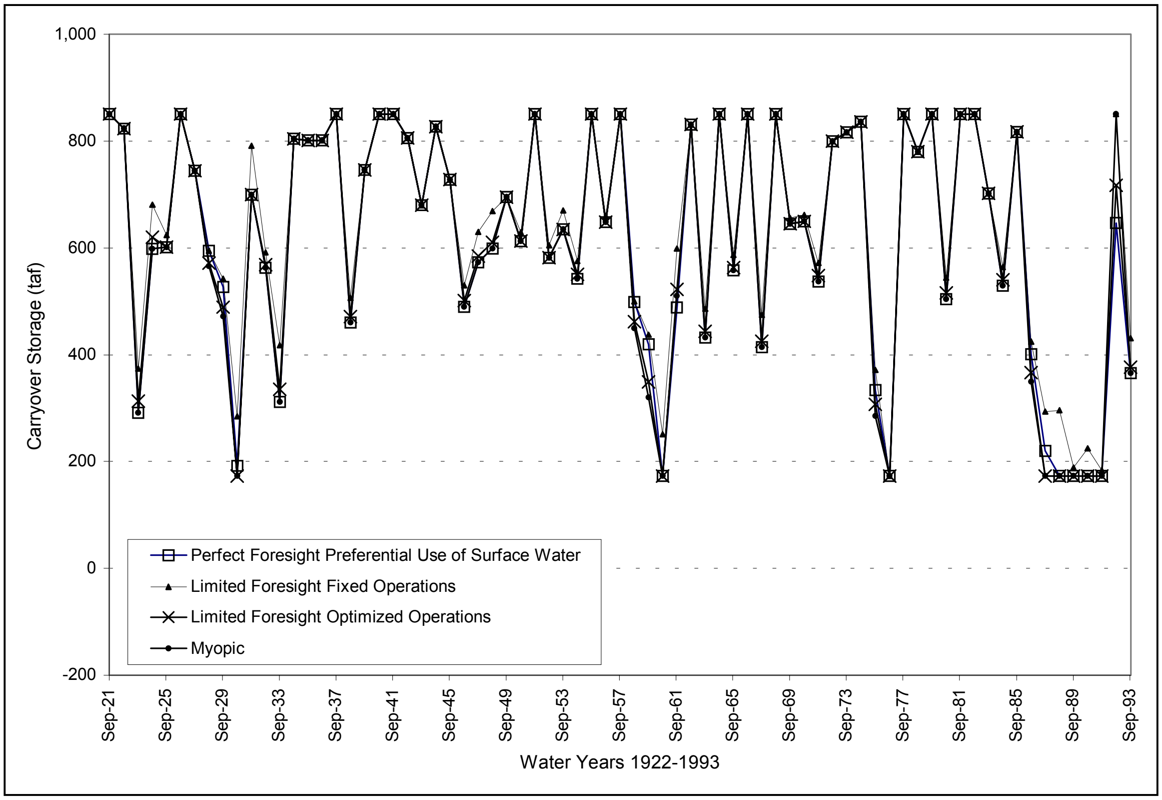

Figure 7.11 Reservoir Storage under Groundwater Banking

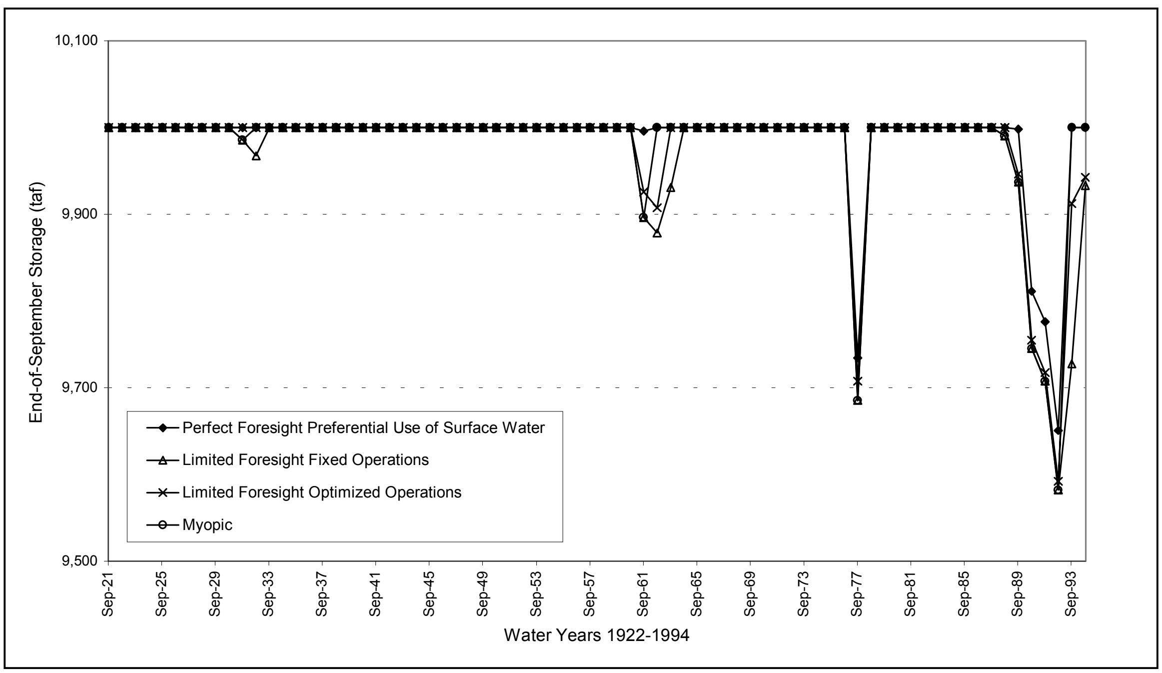

Figure 7.12 Banked Groundwater Storage

A technique for running network flow or more general linear programming models with limited foresight is described in Chapter 4. This chapter applies the technique to a simple reservoir-aquifer system. The objective function is to minimize the combined operating and water shortage costs over the period-of-analysis. Results from this simple analysis show the importance of modifying reservoir carryover storage rules or penalties to account for groundwater supplies. The following general conclusions are inferred.

(1) The perfect foresight aspect of traditional ISO models can substantially under estimate shortages and shortage costs compared to more realistic reservoir operation prescribed using the limited foresight model or the more myopic standard linear operating policy, especially in the absence of groundwater storage (see Figure 7.2).

(2) Conjunctive use of surface and ground water can substantially improve overall system reliability and reduce total costs. For the case study conjunctive use reduced costs by 36% - 87% depending on the amount of available groundwater and the mode of operation (see Table 7.1).

(3) Carryover storage rules determined without explicitly accounting for the presence of groundwater storage become economically very inefficient as groundwater supplies increase (see Figure 7.3c), and can perform worse than the myopic standard linear operating policy (see Figure 7.3d).

(4) Under conjunctive use the value of surface carryover storage rapidly diminishes in the presence of increasing groundwater supplies (see Figure 7.4).

(5) In systems where surface reservoir spills are negligible, the future benefits of active recharge must be weighed against the additional treatment and extraction costs and the opportunity cost of the recharge water either as reservoir releases or as carryover storage. In systems with significant spills, the opportunity cost may be zero so that active recharge is more attractive. Active recharge can be readily implemented in the limited foresight model for this latter case using a persuasion penalty on deviations of end-of-year groundwater storage from a pre-set target. This target volume or "insurance water" should be sufficient to meet demands in the most extreme hydrologic event. Setting the target to initial storage prevents groundwater mining.

(6) Under conjunctive use, not explicitly changing reservoir rules for carryover storage results in significant additional costs (see Figure 7.3c).

(7) With an active recharge program, perfect foresight results, surprisingly, in less groundwater pumping and greater shortages - although diminished shortage costs (see table 7.3).

(8) Integrated conjunctive use greatly reduces the impact of perfect foresight. Reservoir operations under perfect foresight, limited foresight and myopic

operation become identical except under extreme shortages (see Figures 7.11 and 7.12).

Though the model presented here is very simple, it can be readily adapted to analyze more complex systems. Many additional facets could be added to the case study, such as: additional benefits (e.g., hydropower); additional costs (e.g., head dependent pumping); additional constraints (e.g. minimum instream flows). However, it was felt that these would detract from the central purpose of the chapter: to illustrate the effect of conjunctive use on optimal reservoir release rules. Similarly the lumped parameter representation of groundwater could be replaced with a more detailed model using the response matrix approach. The use of integer linear programming rather than the more restrictive network flow algorithms would make the method better suited to capacity expansion problems.

For simple systems, implicitly stochastic optimization models run with limited foresight have few advantages over stochastic linear or dynamic programming. Stochastic models allows a better understanding of decision-making under uncertainty. However many difficulties remain concerning the development of a reliable stochastic hydrology, and for complex systems the resulting explicitly stochastic models are difficult, if not impossible to solve using traditional methods. It is in this situation that the demonstrated limited foresight model is most useful. Results show that the perfect foresight attribute of deterministic models is probably not significant under conjunctive use operations. The larger issue is whether conjunctive use, so easily implemented in a model, can be realized in real-world operating policies with real institutional constraints.

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8. CONCLUSIONS

Computer models are routinely used to help plan and manage complex water resources systems. A combined simulation-optimization approach facilitates the screening and study of alternatives. Detailed simulation models evaluate the consequences of a set of decisions or set of operating rules (what-if analysis. Optimization models, though representing the system in a more simplified manner, prescribe operations that best meet a pre-defined objective. They provide points of departure for more detailed analysis.

Planners and operators must make decisions with uncertain knowledge of future supplies and demands. Stochastic modeling approaches would therefore seem more appropriate. However for large multi-reservoir systems explicitly stochastic approach may be unrealistic. Mathematical hydrologic models may inadequately capture the complex auto- and cross-correlation structure of system flows. Solution of large stochastic problems with many state variables may be computationally impractical. Deterministic approaches are therefore more frequently applied. Where the historic flow-record is sufficiently long it may be used directly as representative of the range and variations in flow, and is so implicitly stochastic.

Implicitly stochastic optimization (ISO) models prescribe system operations for a deterministic set of input or control variables. Though relatively easy to construct, model results are influenced by future knowledge of all control variables over the period-of-analysis. This property, commonly referred to as perfect foresight, distorts reservoir operations and may significantly misrepresent the value of both existing and planned facilities and any proposed changes to system operation. This dissertation presents a new limited foresight model that overcomes the problem of perfect foresight and incorporates risk aversion in the prescribed reservoir operation. The proposed method is implemented using sequential runs of an ISO model, where each run has an optimized ending or carryover storage value function. The time horizon for each run is reduced to a fraction (1/n) of the period-of-analysis. The series of n linked consecutive runs form the optimal operating policy over the entire period-of-analysis. An iterative non-linear search algorithm is used to define the optimal carryover storage value function. Balancing rules are used to reduce the dimensionality of the multi-reservoir operation problem. The method can also be used for conjunctive use studies. The valuation of carryover storage forms an implicit operating rule for over-year storage.

From a series of simple case studies the following conclusions are drawn.

1. For simple systems, implicitly stochastic optimization models run with limited foresight have few advantages over stochastic linear or dynamic programming.

2. The perfect foresight of deterministic optimization models may significantly distort reservoir operation where reservoirs are used for over-year storage, and where multi-year droughts occur.

3. The impacts of perfect foresight are revealed by the lack of hedging under average hydrologic conditions and the much more aggressive hedging during the latter years of an extended drought.

4. As system storage increases the effects of perfect foresight are diminished.

5. The limited foresight model results in an economically derived value of carryover storage.

6. The limited foresight model prescribes more realistic reservoir operations and is more likely to be acceptable to stakeholders skeptical of policies derived from perfect foresight.

7. Differences in operation between the limited and perfect foresight model are typically minor except prior and during drought conditions when differences can have significant economic impacts.

8. The perfect foresight models can substantially under estimate shortages and shortage costs compared to more realistic reservoir operation prescribed using the limited foresight model or the more myopic standard linear operating policy, especially in the absence of groundwater storage.

9. There exists a wide range of near-optimal carryover storage policies.

10. Operating rules may be more easily deduced from the limited foresight model.

11. The limited foresight model can quantify the over-achievement of perfect foresight models.

12. Where hydrologic models inadequately capture the persistence of drought phenomena, the limited foresight model will prescribe more conservative release policies than its explicitly stochastic counterpart.

13. Simple reservoir balancing rules can be used to reduce the dimensionality of a multi-reservoir operation problem.

14. Reservoir performance might be improved through the use of higher order polynomials to represent the carryover storage function.

15. Considerable benefits may accrue by explicitly adjusting surface reservoir operations to account for contingent groundwater supplies.

16. Carryover storage rules determined without explicitly accounting for the presence of groundwater storage become economically very inefficient as groundwater supplies increase and can perform worse than the myopic standard linear operating policy.

17. Conjunctive use of surface and ground water can substantially improve overall system reliability and reduce total costs depending on the amount of available groundwater.

18. Under conjunctive use the value of surface carryover storage rapidly diminishes in the presence of increasing groundwater supplies.

19. Integrated conjunctive use greatly reduces the impact of perfect foresight. Reservoir operations under perfect foresight, limited foresight and myopic operation converge except under extreme shortages.

APPENDIX A. THE NELDER-MEAD SIMPLEX METHOD

The simplex method for function minimization was first suggested by Spendley et al. (1962) and later developed by Nelder and Mead (1965). The method is applicable to minimization of unconstrained mathematical functions of several variables. It is a zero-order search method, not requiring evaluation of the function gradient.

A simplex is a geometric figure formed by a set of n+1 points in n-dimensional space (Rao 1996). In the simplex method, the coordinates of each vertex define possible sets of input variables. The function is evaluated at the n+1 vertices of the simplex and subsequently the simplex is moved towards the optimal point through an iterative process. At each iteration, the value of the function at the vertices defines the direction of movement with the replacement of one or more of the original vertices by new points with lower function values.

Consider the minimization of a function with n variables. An initial set of (n+1) points, x_1, $x_2 \ldots x_n$, are chosen so that they form a simplex. The objective function is evaluated at each vertex and the vertices are subsequently ranked in accordance with the value of the objective function and relabeled. The vertex corresponding to the highest value of the objective function is labeled x_h, the second highest is labeled x_s and the vertex with the lowest function value is designated x_l, so that:

$$f(x_h) = \max_i [f(x_i)] \qquad \text{(A1)}$$

$$f(x_s) = \max_i [f(x_i)] \quad i \neq h \qquad \text{(A2)}$$

$$f(x_l) = \min_i [f(x_i)] \qquad \text{(A3)}$$

In addition to the vertices, an $(n+2)^{th}$ point x_c is defined as the centroid of the n vertices for $i \neq h$.

The simplex is moved using one of three operations known as reflection, contraction and expansion. Each operation aims to replace x_h by a vertex that has a lower function value. Under the reflection process x_h is replaced by a new vertex x_r that is the reflection of the vertex x_h in the hyperplane formed by the remaining vertices. For the case of a two dimensions simplex, the reflection point is located along a line from x_h through the centroid of the line joining x_r and x_l. The j^{th} coordinate of the centroid is given by:

$$x_{c,j} = \frac{\sum_{i=1}^{n+1} (x_{i,j} - x_{h,j})}{n} \quad j = 1,2,...n \qquad \text{(A4)}$$

The location of the reflection point is given by:

$$x_r = x_c + \alpha(x_c - x_h) \qquad \text{(A5)}$$

where the reflection coefficient, α, is defined as:

$$\alpha = \frac{\text{distance between } x_r \text{ and } x_h}{\text{distance between } x_h \text{ and } x_c} \qquad \text{(A6)}$$

If the value of the function at x_r lies between x_h and x_l, x_h is replaced by x_r and a new simplex is created. Alternatively, if a reflection process results in a new minimum point x_r such that $f(x_r) < f(x_l)$, the function value can be expected to decrease further by moving further in the direction of the vector x_h to x_r. Consider an expansion point x_e defined by:

$$x_e = x_c + \gamma(x_r - x_c) \qquad \text{(A7)}$$

The expansion coefficient, γ, is defined as:

$$\gamma = \frac{\text{distance between } x_e \text{ and } x_c}{\text{distancebetween } x_r \text{ and } x_c} > 1 \qquad \text{(A8)}$$

If $f(x_e) < f(x_l)$, the simplex is expanded with the replacement of x_h by x_e to form the new simplex. The expansion process reduces the number of iterations required to move the initial simplex to the vicinity of the optimal solution.

Using only the reflection and expansion process to move the simplex can, in some cases, cause the iterative procedure to cycle with the simplex rotating around the optimal location. The accuracy of the solution is also limited by the initial size of the simplex. To avoid the problem of cycling and to provide greater accuracy, a contraction procedure is introduced. This process either launches the simplex in a new direction to overcome, the problem of cycling, or contracts the simplex in the vicinity of the optimal solution to provide greater accuracy. A contraction is initiated when the function value at the reflection point is greater than all other vertices except x_h, i.e.

$$f(x_r) > \max_i[f(x_i)] \quad i \neq h \qquad \text{(A9)}$$

The new contracted simplex may either lie within or be external to the original simplex. The contracted simplex may share either one or all but one of the vertices of the original simplex. If $f(x_r) > f(x_h)$, then the new contracted simplex lies within the original simplex.

A contraction point, x_{co}, is defined dependent on the relative magnitudes of $f(x_r)$ and $f(x_h)$:

For $f(x_r) > f(x_h)$: $\qquad x_{co} = x_c + \beta(x_h - x_c) \qquad$ (A10)

For $f(x_r) <= f(x_h)$: $$x_{co} = x_c + \beta(x_r - x_c) \quad \text{(A11)}$$

where the contraction coefficient, β, is defined as:

For $f(x_r) > f(x_h)$: $$\beta = \frac{\text{distance between } x_c \text{ and } x_{co}}{\text{distance between } x_c \text{ and } x_h} < 1 \quad \text{(A12)}$$

For $f(x_r) <= f(x_h)$: $$\beta = \frac{\text{distance between } x_c \text{ and } x_{co}}{\text{distance between } x_c \text{ and } x_r} < 1 \quad \text{(A13)}$$

If $f(x_{co}) <= f(x_h)$, then x_h is replaced by x_{co} to form the new simplex. Alternatively, if $f(x_{co}) > f(x_h)$, the new simplex shares only the vertex x_l with the original simplex. The new vertices are given by:

$$x_j = \frac{x_j + x_l}{2} \quad j = 1,2,...n \quad \text{(A14)}$$

Figure A-1 illustrates the possible range of reflections, expansions and contractions in two-dimensional space. Seven possible case have been identified which result in five possible outcomes:

- $f(x_r) < f(x_l)$ and $f(x_e) < f(x_l)$: expansion (Figure A-1, Case A)
- $f(x_r) < f(x_l)$ and $f(x_e) >= f(x_l)$: reflection (Figure A-1, Case B)
- $f(x_r) >= f(x_l)$ and $f(x_r) <= f(x_s)$: reflection (Figure A-1, Case C)
- $f(x_r) > f(x_s)$ and $f(x_r) <= f(x_h)$: contraction, new vertex lies outside simplex
  - $f(x_c) <= f(x_r)$: contraction type 1 (Figure A-1, Case D)
  - $f(x_c) > f(x_r)$: contraction type 2 (Figure A-1, Case E)
- $f(x_r) > f(x_h)$: contraction, new vertex lies inside simplex
  - $f(x_c) > f(x_h)$: contraction type 3 (Figure A-1, Case F)
  - $f(x_c) <= f(x_h)$: contraction type 4 (Figure A-1, Case G)

Case B and C result in identical operations. The method is assumed to have converged when the standard deviation of the function at the n+1 vertices of the current vertex is smaller than some specified tolerance, ε:

$$\left\{ \sum_{i=1}^{n+1} \frac{[f(x_i) - f(x_c)]^2}{n+1} \right\}^{1/2} \le \varepsilon \qquad \text{(A9)}$$

This criterion is concerned with the variation of the function rather than with changes of the function inputs. Convergence depends on the simplex not becoming small compared with the curvature of the functional surface until the final minimum is reached. If the curvature is marked there is justification in continuing the search to refine the position of the minimum. Nelder and Mead (1964) recommend values of $\alpha = 1$, $\beta = 0.5$, and $\gamma = 2$, to minimize the number of iterations required for convergence.

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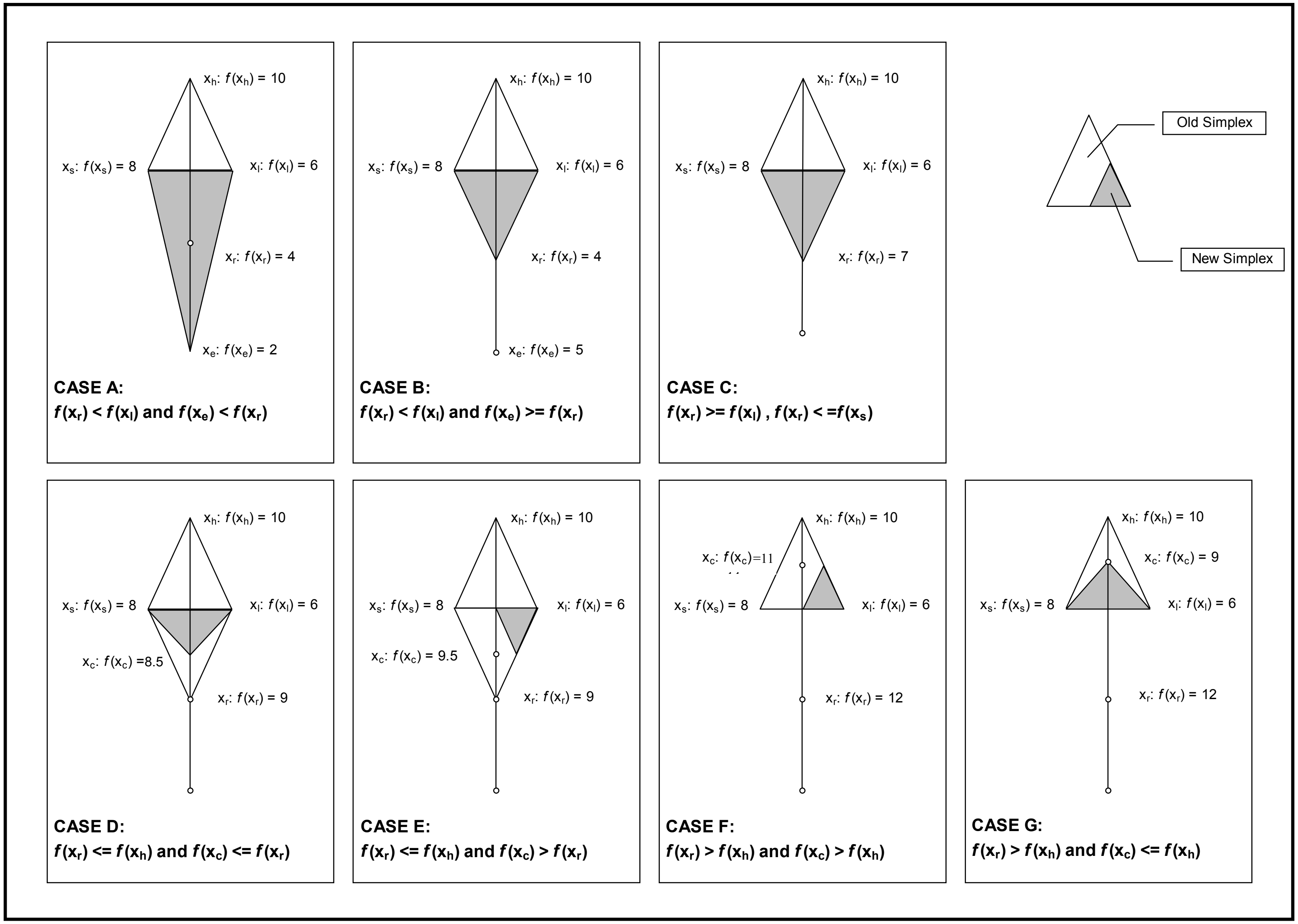

Figure A.1 Reflection, Expansion and Contraction Operations under the Nelder-Mead Simplex Method