Optimal Hydropower Reservoir Operation with Environmental Requirements

By

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Abstract

Engineering solutions to the environmental impacts of hydropower operations on downstream aquatic ecosystem are studied using revenue-driven optimization models.

Peaking hydropower operations affect stream ecosystems by abruptly changing flow conditions. Operations are often restricted by minimum releases to a sensitive stream and maximum rates of change, or ramping rates, of releases. These constraints potentially reduce the economic value of daily generation by reducing operational flexibility. A linear programming model for the hourly operation of a reservoir-afterbay hydropower complex was formulated and solved for parametrically varying levels of environmental constraints. Consistent with the short time scale, the model assumes constant head and perfect knowledge of energy prices. Results indicate that environmental restrictions on releases can reduce revenues by 15% without an afterbay. Optimally operated, an afterbay reduces this cost considerably, even by half. Several alternative release patterns to the stream were identified for a given revenue level.

To bridge the gap between hourly operations and planning models, this work develops a method to incorporate information on hourly energy prices into revenues for hydropower reservoir optimization models with larger time steps (weekly, monthly, etc). The method, which derives a simple equation for revenue, assumes a known frequency curve for hourly prices during the period of interest and an operational strategy that allocates water release in order of decreasing hourly price, as in peaking operations. The estimated revenue was compared with the optimal revenue obtained from the solution of the hourly optimization problem. Results show a very small approximation error (less than 1%) when a price frequency curve with fine resolution is available. The method was extended to the case with minimum instream flow requirements and the approximation proves to be as good as in the unconstrained case.

Thermal stratification during summer is a condition typically observed in hydropower reservoirs. The operational problem is usually the early exhaustion of the cold water present in the reservoir because water is released from the lower depths of the reservoir throughout the season. This causes warm releases through the rest of the season, when air temperatures are typically highest and aquatic ecosystems are at highest risk. A model was developed for the optimal operation of a reservoir with selective withdrawal aimed to make operations more flexible during the summer. Operational decisions are releases from the cold and the warm water pool during each week in the stratification season. Environmental constraints are represented by minimum required releases to the stream and maximum allowed temperature of releases. Hydrologic uncertainty is modeled through an ensemble of 25 series of weekly net inflows to the reservoir. The dynamics of the thermal structure of the reservoir was simplified by considering two pools, a warm upper layer and a cold lower layer, with exogenous temperature. The model is solved by an implicit variant of Sampling Stochastic Dynamic Programming (SSDP) with continuous approximation of the value function by Chebyshev polynomials. Selective withdrawal allows for cold water hedging from early in the stratifications

season towards the end, when the upper layer of the reservoir is warmest. To avoid a myopic behavior, the value of carryover storage at the end of the summer was estimated by application of value iteration in a dynamic programming model. The state of the reservoir was represented by the total storage and the cold water storage. At each week of the season, given a total storage and its percentage of cold water, the model solves for optimal release from each of the two pools by trading off the immediate benefit of power generation and the future value of leaving water in storage, both warm and cold. Results show a much stronger effect of total storage than cold water storage on the economic performance and operational pattern of the reservoir. As expected, total hydropower generation and revenues increase with total storage. Cold water storage affects operations and therefore revenues only when it is at its minimum feasible level (i.e. only the minimum flow can be released at the appropriate temperature) or when energy prices are very high. No effects are observed early in the season, when the upper layer is still cooler than the temperature target. Future enhancements are proposed to overcome the limitations imposed by the approximation scheme adopted for the future value function.

This dissertation shows that engineering solutions, in concert with optimized operational decisions, can effectively add flexibility to hydropower operations under environmental constraints, reducing the compliance cost.

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION: THE CONFLICT BETWEEN HYDROPOWER OPERATIONS AND ECOSYSTEM MAINTENANCE

Water resources management often must deal with several conflicting water uses under highly uncertain conditions. Conflicts between traditional uses like hydropower, and domestic and irrigation water supply have been resolved at least partially in the past. The situation changes drastically when no common performance measure can be established for conflicting objectives. This is the case of environmental impacts associated with reservoirs built to support traditional water uses like irrigation, urban and industrial water supply, and hydropower. Dams are a physical barrier in the river system, whose effects, besides the obvious change from a stream to a lake environment in the reservoir itself, are related to the change in the flow regime (at different time scales), water diversion from the river channel, blockage of downstream flows of nutrients and sediments, change in water temperatures and oxygen levels, and impeding fish and wildlife migration (Petts, 1989).

Hydropower is a relatively cheap source of electricity, with variable operational costs in the order of 5 $/MWh, as compared to 20 $/MWh of fossil fuel steam plants, and 28 $/MWh for gas turbine peaking units (Harpman, 1999). However, the effects of construction and operation of hydropower reservoirs on downstream aquatic/terrestrial ecosystems are a major concern (Richter and Thomas, 2007). Due to its ability to quickly and inexpensively respond to short-term changes in demand, hydropower reservoirs often are operated to provide power during periods of peak demand. This operation scheme, known as hydropeaking, contrasts with the lack of flexibility associated with thermal units which cannot respond as quickly to ramping requirements (Svoboda *et al*., 1997). Base load is provided by the least expensive thermal units, but at some demand levels, the marginal costs of thermal generation become very high, and hydropower units are required. Peaking operations cause large abrupt flow variations downstream of powerhouses, which can harm river and streamside ecosystems. The effects of short-term, hydropeaking operations on aquatic ecosystems are not well understood, although reduction in native species richness has been observed (Vehanen *et al*., 2005). Hydropeaking also can conflict with downstream cold water fisheries (Krause *et al*. 2005). A key aspect of the problem is the spatial and temporal scales involved. Hydropower scheduling takes place at monthly, weekly, daily and hourly intervals, and operations at each level affect different environmental processes. The increased variability associated with hydropeaking does not help to mitigate the loss of hydrologic variability at larger time scales, which controls the diversity of aquatic fauna (Moyle and Mount, 2007).

Due to these conflicts, hydropower operations are regulated to reduce or mitigate negative impacts. The regulatory framework for the operation of hydropower facilities varies throughout the world. In Sweden, licenses to build and operate dams are perpetual, although operating conditions may be reviewed in accordance with regulations

(Svensson, 2000), and operational changes involving production losses up to 5% are enforced without compensating the hydropower operator. In the United States, the main regulatory instrument is the licensing system administrated by the Federal Energy Regulatory Commission (FERC). Licenses are granted for 30 to 50 years and establish, among other aspects, operational restrictions on the generator. These restrictions seek to consider the effects of hydropower operations on activities or interests that might be affected, including commercial and recreational fisheries, recreation, and ecosystem conservation. Traditionally, environmental considerations are included in the licenses in the form of minimum releases to a sensitive stream, bounds on flow changes, and specific water quality requirements in the reservoir itself and downstream. These operational restrictions limit the ability of the system to follow the pattern of energy prices and can reduce the economic value of energy generation.

Environmental constraints impose a cost on hydropower producers. Harpman (1999) estimated a reduction of 8.8% in the short-run economic value of hydroelectricity under specific flow constraints on Glen Canyon Dam on the Colorado River. More recently, Kotchen *et al*. (2006) carried out an ex post benefit-cost analysis of a dam relicensing agreement in Michigan and found that the social benefits more than double the producer costs. In Sweden, a constant flow of 1 cubic meter per second can be worth about 41,000 US$/year. The magnitude of economic losses in terms of hydropower production from minimum releases led to the exploration of alternative means other than water releases from reservoirs to achieving an ecosystem goal, including changes in channel structure, defined as biotype adjustments (Svensson, 2000).

Engineering solutions can reduce the burden on producers, and therefore the conflict between environmental and economic performance, by adding operational flexibility. For example, Richter and Thomas (2006) suggest the use of a water storage facility downstream of a power house to re-regulate the release pattern. Such an alternative typically exists in cascade hydropower systems, where the most downstream reservoir can serve this purpose. In some systems, afterbays have been created for this purpose. When temperature management in the reservoir and releases is relevant, a temperature control device (TCD) can be introduced. The most practical and widely adopted method for the case of a stratified reservoir is selective withdrawal, which consists of strategically located outlets to allow releases from different zones of the reservoir (Cassidy, 1989). Computer models allow evaluation of the performance of such engineering solutions in economic and environmental terms.

The complexity that needs to be captured in models increased since many countries in the world have established electricity markets. Before energy market liberalization, the problem was formulated as cost minimization by a central utility planner (Jacobs and Schultz, 2002). With energy markets and decentralization of electricity generation authority, revenue maximization has become the driver for operations. However, little effort has been devoted to develop an appropriate representation of energy prices, the main outcome of energy markets, for modeling purposes. Some work has been directed to developing statistical price forecasting models (e.g. Nogales *et al.*, 2002) and explicit economic models of electricity markets, including optimal bidding strategies for generators under perfect competition (Pritchard *et al*. 2005) and duopolistic models (Scott and Read, 1996). Unfortunately, the water resources community still relies on simplistic representations of energy prices for planning models, assuming either an average price for each decision period or a two-part (peak/off-peak) approximation of the price variability.

The objective of this dissertation is to study, through the use of revenue-driven optimization models, the effects of some engineering solutions as mitigation for the negative impacts of hydropower reservoir operations on downstream ecosystems. Emphasis is on the economic and environmental performance of solutions, as well as operational insights. This dissertation has six chapters, structured as follows:

- Chapter 2 includes background on four topics that conform the basis for the following chapters,
- Chapter 3 presents the study of hourly hydropower operations during a typical summer day for a reservoir-afterbay system. This chapter includes the formulation and solution of a deterministic linear programming model, which relies on the assumption of constant head. Discussion includes hydropower revenues, afterbay operational insights, and resulting instream flow patterns,
- Chapter 4 employs a duration curve of hourly energy price and the hydropeaking assumption to derive a closed form expression for hydropower revenues realized at coarser time scales. The approach is extended for the cases of variable head and when a minimum release requirement is imposed,
- Chapter 5 includes development of a dynamic programming model for the operation of a thermally stratified reservoir with selective withdrawal. Release temperature control is aimed to support a cold water fishery during the summer under hydrologic uncertainty,
- Chapter 6 summarizes the most relevant insights and conclusions of this dissertation. Future work and possible enhancements are also identified.

Each chapter is self-sustained and includes its own references and conclusions.

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CHAPTER 2

RELEVANT BACKGROUND

The relevant literature presented herein includes four main topics. The first subsection introduces models for the optimal operation of hydropower reservoir systems. It describes in detail how optimization techniques have been used to assist reservoir managers and operators on how much power to produce, or equivalently, how much water to release from a reservoir, at a given point in time. The second subsection describes different methods utilized to quantify the effects of river regulation, particularly due to hydropower operations, on downstream ecosystems. These approaches include the establishment of minimum instream flows, determination of the degree of hydrological alteration with respect to the unimpaired flow regime, and the use of fish population models when aquatic species conservation is the main goal. The third topic includes current knowledge on the ecosystem effects of hydropower operations. The final subsection discusses examples of studies where tradeoffs between ecosystem and other water uses are explicitly explored. Each subsection includes a final summary and identification of critical issues to be faced in the proposed study.

2.1 Optimal Operation of Hydropower Reservoirs

An extensive literature exists on the application of optimization techniques to the operation of hydropower reservoir systems. Studies vary in several ways, including the objective optimized, time horizon for optimization (long- vs. short-term), system size and configuration, and the representation of uncertainty. These factors determine the optimization techniques most suitable for each case. This review focuses on studies where hydropower generation is the primary objective to be optimized. This focus still includes multi-purpose reservoirs whose primary purpose is water supply and hydropower, where hard constraints are imposed to satisfy non-hydropower requirements.

Before market liberalization, power generation was typically controlled by a centralized public agency, with the objective of meeting demand at minimum cost. Under those conditions, operations planning represented a large-scale optimization problem, usually involving several alternative power sources. In general, the water resources literature focuses on planning studies rather than short-term scheduling, with monthly or weekly decision intervals, to minimize the total cost of alternative power sources. Sometimes, a penalty for unmet demand is included, i.e. power demand is modeled as a soft constraint of the problem. Constraints include physical infrastructure capacity and operational restrictions resulting from the regulatory framework.

Hydrologic conditions (particularly inflows) and power demand (or price, after market reform) are the two main sources of uncertainties, the latter often neglected in the water resources literature. When hydrologic uncertainty is considered, optimization techniques are used to determine operating rules which suggest the optimal releases at each decision period as a function of the information available, most notably reservoir storage level.

Generation-related objectives take different forms, depending on the spatial and temporal scales considered. For large-scale hydro-thermal systems with centralized decisions, the objective is usually expressed as minimizing penalties from demand unmet by the hydro plants (e.g. Turgeon, 1980, 1981a; Pereira and Pinto, 1991; Saad *et al*., 1994 and 1996; Tejada-Guibert *et al*., 1995). These penalties can involve both the cost of thermal generation and losses from power outages.

The two most widely used techniques applied for long-term models are linear programming (LP) and dynamic programming (DP) (Yakowitz, 1982; Labadie, 2004). DP is particularly suitable when dealing with sequential decision processes (Bellman, 1957; Bertsekas, 1976) and presents several advantages, including its capability to handle nonlinear objectives and complex constraint sets, and its assurance of globally optimal solutions (Bertsekas, 1976). The method relies on Bellman's Principle of Optimality which asserts that "…an optimal policy has the property that, whatever the initial state and optimal first decision may be, the remaining decisions constitute an optimal policy with regard to the state resulting from the first decision" (Bellman, 1957 pp. 83). Based on this principle, a multistage optimization problem is divided into a sequence of single-stage sub-problems. In the case of hydropower reservoirs the problem is stochastic and can be highly nonlinear (Yakowitz, 1982) so DP is the appropriate choice. Moreover, dynamic programming presents the unique feature (only shared by optimal control theory) to provide optimal feedback policies (Bertsekas, 1976; Labadie, 2004).

Single reservoir, deterministic models are the simplest. The deterministic assumption relies upon the certainty equivalence principle (Bertsekas, 1976; Yakowitz, 1982). This principle assumes the expected value of the performance criterion can be obtained by assuming that random variables take their expected values. However, this assumption often leads to suboptimal solutions that can be far from the optimum (Bertsekas, 1976; Philbrick and Kitanidis, 1999). A typical DP approach is to discretize the state and decision variables (storage and release, respectively) and solve the Bellman equation (i.e. optimize at each time step) for each discrete value at each stage. This involves, at each stage and for each state value, a search over all possible discrete releases. Nonlinear search techniques cannot be applied in this setting and the problem is essentially an exhaustive search. Finer discretization increases the computational effort.

Hydrologic stochasticity has been incorporated in different ways. At its simplest, temporally uncorrelated probabilities can be assigned to inflows. When hydrologic persistence is considered, hydrologic state variable(s) need to be included, with the previous stage inflow the most typical choice (Little, 1955). Recent applications consider forecasts as a hydrologic state variable (Kelman *et al*. 1990; Karamouz and Vasiliadis, 1992; Kim and Palmer, 1997; Faber and Stedinger, 2001). The version of dynamic programming which explicitly incorporates expectation over random variables is called stochastic DP (SDP), and its performance under alternative choices of hydrologic state variables was studied by Tejada-Guibert *et al*. (1995). They concluded that more complete hydrologic information yields to better performance in cases where severe penalties are applied to shortages. The value of long-term forecasts has been studied in a Bayesian programming framework by Kim and Palmer (1997), and with simulation by Hamlet *et al*. (2002).

Multireservoir problems are much more complex (Labadie, 2004). These complexities include its higher dimensionality and spatial correlations of inflows when stochasticity is explicitly represented. In that case, only discrete-state DP can be successfully applied to determine optimal operating policies (Yakowitz, 1982). The number of discrete searches increases exponentially with the number of reservoirs considered. The exponential growth of computational effort has been widely recognized and defined as the curse of dimensionality by Bellman (1957). This shortcoming typically limits the application of discrete dynamic programming to problems with 3 or 4 state variables.

An approach to avoid the curse of dimensionality in dynamic programming consists in approximating the original multivariate problem to reduce the number of searches. Techniques include aggregation (Masse, 1946; Turgeon, 1980; Saad *et al*., 1994, 1996; Turgeon and Charbonneau, 1998), successive approximation DP (Turgeon, 1980), decomposition (Turgeon, 1981a), and principal component analysis (Saad and Turgeon, 1988; Saad *et al*., 1992). The aggregation/disaggregation approach is the most widely used and consists of solving a problem for a hypothetical composite reservoir, representing the entire system. Then, disaggregating procedures are applied to determine the optimal operation of each individual reservoir.

After an optimal operating policy is determined, its performance can be simulated for a given time period. In the case of discrete SDP, optimal policies are represented by tables containing the optimal release for a finite number of discrete values of the state variable. In real operation, however, the system can be at a state not included in the discretization, and therefore approximations must be made to decide how much to release. A direct choice is to simply interpolate between two states for which the optimal release is know. The other alternative is to reoptimize at each time step, which requires interpolation of the future value function, either in a linear (Pereira and Pinto, 1991) or a nonlinear fashion (Johnson *et al*., 1993; Tejada-Guibert *et al*., 1993). A similar approach was proposed by Braga *et al*. (1991), where a deterministic DP is used to estimate the future value functions, and then a forward procedure finds the optimal release from each reservoir at the beginning of each month.

The water resources literature for short-term scheduling of hydropower is relatively scarce compared with long-term scheduling, with a few exceptions (Turgeon, 1981b; Georgakakos *et al*., 1997a, 1997b, 1997c; Wang *et al*., 2004). However, extensive work exists in the field of electric power systems. Most studies consider the optimal short-term operation of hydropower reservoirs as part of a large-scale hydro-thermal system optimization problem, with deterministic power demands. The role of hydro plants depends on their relative capacity with respect to the thermal units. If the system is predominantly thermal, hydro units are scheduled only for peaking. If the system is hydro-dominated, these plants also contribute to the base load (Wang and Shahidehpour, 1993).

Two general approaches can be identified to deal with hydro-thermal systems. The first approach is to separate the problem into a stochastic long-term hydro-thermal problem and deterministic short-term scheduling. This approach establishes generation (or release) targets for each hydropower plant. This approach is what Masse (1946) calls decomposition into ‘strategic’ and ‘tactical’ problems. Hourly scheduling optimizes week-ahead hydro generation, taking into account head variations and flow routing to meet the target set by the long-term optimization. Turgeon (1981) used the principle of progressive optimality to minimize total production cost (including power imports and exports) of a multi-reservoir system. Yi *et al*. (2003) used a successive approximation DP algorithm to maximize a surrogate for the basin-wide daily operating efficiency. Wang *et* *al*. (2004) applied a direct search method to minimize the total energy generation over the time horizon given the initial and final reservoir storages.

The second approach is to solve the integrated short-term hydro-thermal problem, often called the ‘unit commitment problem’ in power systems jargon. The scheduling of thermal units involves the use of binary variables which establish the state (on-off) of each thermal unit at each time step and are used to include start-up and shut-down costs. This approach can yield better solutions than when hydro and thermal generation are optimized separately (Baldick, 1995). This integrated approach represents a situation when a single operator owns several plants (both hydro and thermal) and important gains can be obtained by coordinated operations. The objective is to minimize the total production cost (including thermal generation and net purchases for interconnected systems) over the horizon (day or week). Studies differ in the level of detail for representing different constraints (e.g. hydro system, thermal ramp constraints, spinning reserve). Solution techniques include linear programming (Piekutowski *et al*., 1994), network flow (Wang and Shahidehpour, 1993; Heredia and Nabona, 1995), dynamic programming (Ouyang and Shahidehpour, 1991), mixed integer linear programming (e.g. Chang el at., 2001), Lagrangian relaxation or decomposition (Ruzic and Rajakovic, 1991; Ohishi *et al*., 1991; Rakic and Markovic, 1994; Baldick, 1995; Guan *et al*., 1997), evolutionary algorithms (Kazarlis *et al*., 1996; Orero and Irving, 1998; Rudolf and Bayrleithner, 1999; Wu *et al*., 2000), artificial neural networks (Naresh and Sharma, 2000), or a combination of techniques (Cheng *et al*., 2000).

With the liberalization of the power sector, power markets started to play a role, defining the value of energy by the spot price and therefore the possible power exchanges among different companies. Markets have been explicitly incorporated in the optimal short-term scheduling problem by Scott and Read (1996), Lino *et al*. (2003), and Pritchard *et al*. (2005).

In summary, long-term operating policies under hydrologic uncertainty can be advantageously derived by stochastic dynamic programming (SDP). Approximations are needed for large-scale systems to overcome the curse of dimensionality. The most suitable techniques for short-term hydro scheduling depend on the particular nature of the problem at hand, including the complexity of the hydro system, the interconnection of the power system, and the existence of power markets. No simple models have been proposed to analyze short-term (hourly) scheduling of hydropower reservoir systems. Also, power demands, or alternatively, energy prices, have traditionally been assumed as deterministic, even in long-term planning models. This assumption is not appropriate in the face of power markets, which particularly influence short-term operations. Uncertainty on energy prices should be incorporated in long-term models.

2.2 Instream Flows and Ecosystem Effects of River Regulation

Reservoir releases determine to a great extent instream flows at dowstream locations. Consequently, the main environmental effect of river regulation in general and hydropower reservoir operations in particular is the alteration of the stream flow regime at various time scales, including seasonal, monthly, daily and hourly. These alterations in turn affect the associated aquatic and riparian ecosystem mainly through habitat quantity and quality, and substrate availability (Valentin *et al*., 1996; Scruton *et al*., 2005). One traditional approach has been to recommend minimum instream flows to be supported by reservoir releases. Another alternative is to compare the altered flow regime with the unimpaired one, and to establish admissible levels of alteration. When fish species are the main concern, flow regimes can be compared using sophisticated habitat-based population models. Knowledge of these approaches will allow us to define which approach is most suitable to be incorporated in our optimization model.

A variety of methodologies have been proposed to establish minimum instream flow requirements (Jowett, 1997). Methods are based on historic hydrology (e.g. Hydrologic Records and Tennant Method), hydraulic considerations (e.g. Wetted Perimeter technique), and flow-based habitat suitability. Hydrologic and hydraulic methods require less understanding of the ecosystem processes and goals, and are less data-intensive than habitat suitability approaches. Incremental flow methods seek to answer the question of what happens to an ecologically relevant parameter, e.g. aquatic habitat, when flow changes (Stalnaker *et al*., 1995).

Among incremental flow methods, the most widely applied is the Instream Flow Incremental Methodology (IFIM) created by the U.S. Fish and Wildlife Service (Bovee, 1982). The IFIM, a data intensive approach, relies on the simulation module PHABSIM, which relates hydraulic conditions in the stream, typically depth and velocity, with habitat suitability for target fish species through two analytical components: stream hydraulics and life stage-specific habitat requirements (Milhous *et al*., 1984). The stream hydraulics component calculates water depth for a given flow and predicts velocities in the cross section. The habitat component assigns habitat suitability to each cell in the cross section and then calculates the weighted usable area (WUA) as a function of discharge.

Unfortunately, IFIM fails to include a temporal dimension in the analysis, missing a link between extreme hydrologic and habitat events (Hickey and Diaz, 1999). It also fails to include the effects of short-term flow fluctuations in the stream (Hunter, 1992), which is a major effect associated with the operation of load-following hydropower systems. To improve applicability of this method, Armour and Taylor (1991) pointed out the need to investigate habitat-population relationships.

Several authors have argued that flow regime aspects other than minimum instream flows be considered, particularly those related with hydrologic variability at different time scales (Richter *et al*., 1996; Poff *et al*., 1997). Hydrologic variability controls geomorphological processes that affect aquatic ecosystems in the long run. Dams alter geomorphology by changing the relationship between sediment supply and transport capacity. When the lack of high flows leads to fine sediment accumulation downstream, the action of natural floods to remove fine sediments can be mimicked by controlled reservoir releases, or flushing flows (Wilcock *et al*, 1996). Hill *et al*. (1991) proposed consideration of channel maintenance flows, riparian flows and valley maintenance.

An alternative approach to study the effect of river regulation on the flow regime is to compare pre- and post-dam hydrologic conditions. Richter *et al*. (1996) proposed to compare 32 ecologically significant hydrologic attributes grouped in five categories, including magnitude of monthly flows, magnitude and duration of annual extreme water conditions, timing of extreme water conditions, frequency and durations of high and low pulses, and rate and frequency of water condition changes. An application of this method considers the definition of flow management targets based on small variations around the values of the 32 parameters in natural flow regime (Richter *et al*. 1997). Similarly, Poff *et* *al*. (1997) propose that the ecological integrity of the system is controlled by five components of flow regime: flow magnitude, frequency of high and low flows (and other ecologically significant flows), flow duration, flow timing, and rate of change between flow magnitudes. A somewhat narrower approach explores the role of disturbances, defined as extreme, low-frequency events on the ecosystem, and time scale differences between disturbances and life spans of target species (Resh *et al*., 1988).

Hydropower operations can affect several components of flow regime. In particular, short term load-following affects the rate and frequency of changes in flow magnitude. On the other hand, the relevance of each flow regime attribute depends on the specific ecosystem under consideration. For instance, in the Lower Roanoke River, where riparian wetlands constitute a primary concern, the duration of high water episodes is critical (Pearsall *et al*. 2005). Unfortunately, a sound selection of the essential features of flow variation to be included in impact studies is complicated due to the lack of quantitative relationships between parameters of hydrologic variability and its effect of river health (Jager and Smith, 2008).

The temporal dimension of instream flows and its effect on fish habitat was studied by Stalnaker *et al*. (1996). They emphasized seasonal and interannual flow variability, and the effect of alternative regimes on the frequency and timing of habitat bottlenecks. The authors propose to develop flow-based habitat time series and to perform statistical analysis, including the development of habitat duration curves.

One step beyond habitat models are habitat-based quasi-population models of fish species. All these models rely on habitat-flows relationships. Simple versions derive populations estimates based on physical habitat conditions and few empirical parameters (e.g. Harpman *et al*., 1993, Cardwell *et al*., 1996) and can be viewed as a direct extension of habitat-based models. More sophisticated, dynamic models have also been proposed, but their calibration relies heavily on long-term and intensive monitoring efforts. Examples of these models are SALMOD (Bartholow *et al*., 1993), which simulates salmonid population at weekly level, considering multiple habitat types and fish life-stages; and the ORCM (Jager *et al*., 1997) which simulates Chinook salmon during one biologic cycle (from spawning to out-migration) and relies on similar inputs as SALMOD.

In summary, no method is universally accepted by the scientific community to determine instream flow requirements for ecosystem purposes, and therefore to prescribe desirable reservoir release patterns. This is in part due to the dependence on particular conditions and objectives, and also because of the high degree of uncertainty that remains regarding the effects of flow regulation on ecosystems (Castleberry *et al*., 1996; VanWinkle, 1997; Jager and Smith, 2008). In practice and despite its drawbacks, the most widely used method is PHABSIM, which simply establishes minimum instream flows.

2.3 Effects of hydropower operations on ecosystems

The effects of hydropower operations on aquatic and riparian ecosystems have been studied by comparison of regulated and non-regulated rivers (e.g. Bain *et al*., 1988), or by exploring a limited set of operation schemes through simulation (e.g. Krause *et al*., 2005; Scruton *et al*., 2005).

The effects of short-term, hydropeaking operations on aquatic ecosystems are not well understood, although reduction in native species richness has been observed (Vehanen *et al*., 2005). Experimental studies in real settings have concluded that hydropeaking affects movement patterns of fish, and that hydraulic refugia availability are crucial for fish to withstand flow and habitat fluctuations (Valentin *et al*., 1996; Scruton *et al*., 2005).

In some cases a hydropower reservoir can create coldwater fisheries, although a hydropeaking operations work against that purpose (Krause *et al*. 2005). Moyle and Light (1996) concluded that flow regime controls the success of species invasion in California streams. The thermal effects of alternative flow scenarios to enhancing a trout fishery in eastern US were studied by Krause *et al*. (2005). They concluded that different flow regimes perform better with respect to various specific temperature-related objectives, like maximizing the occurrence of optimal grow temperatures or minimizing temperature fluctuations.

To summarize, studies agree that hydropower operations have a negative effect on fish population, especially native species. No universally accepted predictive tools exist to quantify the effects of hourly flow changes on the ecosystem, particularly on fish populations. This relationship is crucial for the application of an optimization model for hydropeaking operations, because the effects of reservoir releases on the ecosystem define both the dynamics of the ecosystem state and also the value of possible ecosystem performance indicators. Beyond static habitat approaches (like PHABSIM), little agreement exist regarding what tools to use. Therefore, the traditional and robust approach of setting simple environmental constraints, like minimum releases to a stream, maximum rates of change in short-term operations, and maximum temperature of releases is adopted in this dissertation. Presumably, complexity can be added as part of future work.

2.4 Tradeoffs between human and ecosystem objectives

Due to the evident difficulty to relate hydropower operations with specific ecosystem performance indices, few studies have explicitly incorporated environmental objectives into water management decisions. In the case of optimization models for hydropower, environmental objectives are assumed as constraints, usually in the form of minimum releases.

Hickey and Diaz (1999) integrated several software packages to explore the tradeoffs between economic benefits and fish population for five alternative flow regimes. The model includes a water allocation, temperature, habitat and salmonid population (SALMOD) modules. A contingent valuation method was used to convert fish population into dollars.

Multiobjective optimization methods identify optimal decisions when conflicting objectives are explicitly incorporated. These methods identify non-inferior solutions, i.e. points at which it is not possible to improve one objective without worsening another. The set of points representing the value of each objective for each of those alternative solutions is called a tradeoff curve or Pareto front (Ko *et al*., 1992).

Cardwell *et al*. (1996) considered the objectives of minimizing water supply shortages and maximizing the number of fish outmigrants that could be supported by a given flow during a month (Cardwell *et al*., 1996). The authors determine habitat area available at different flow levels using the IFIM methodology. Those values are then combined with habitat needs of various life stages (spawning, fry and juvenile) and translated into habitat capacity, an index representing the maximum number of fish that could be supported at the corresponding instream flow. For each choice of the relative importance of the objectives, four sets (one per each hydrologic year type) of monthly minimum inflows are generated. Suen and Eheart (2006) developed a multiobjective model where ecosystem objectives are represented by fuzzy membership functions based on the intermediate disturbance hypothesis. This allows consideration of several parameters of flow regime, similar to those included in the Index of Hydrologic Alteration.

There is an important difference in the interaction between environmental flow requirements and human needs for agricultural, domestic, and industrial uses and hydropower production. In the former, water diverted from the reservoir for water supply does not contribute to environmental flows, whereas water diverted for hydropower production returns to the river at a point downstream the reservoir. Therefore, conflicts between instream flow needs and hydropower production include not only the amount of water available, but also the timing of releases. This issue is less critical when the reservoir is used for water supply, because water deliveries from a reservoir do not need to match demands in real time.

In summary, few studies have explored tradeoffs between ecosystem and other beneficial water uses. Multiobjective optimization techniques have been applied to water resources systems. However, ignorance regarding the effect of different operational schemes on desirable ecosystem outcomes prevents us from representing ecosystem considerations as objectives.

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CHAPTER 3

RE-REGULATION OF HOURLY HYDROPOWER RESERVOIR OPERATIONS

3.1 Introduction

Hourly operations of hydropower reservoirs often involve sudden changes in releases associated with the hourly fluctuations in energy prices. This release pattern, known as hydropeaking, affects stream ecosystems by changing flow conditions on short time scales (Flug, 1997). Within the Federal Energy Regulatory Commission (FERC) licensing process in the United States, operations are often restricted by limiting rates of change of reservoir releases and by setting minimum releases to the stream. Although more sophisticated approaches to instream flow regime alteration have been recently developed (Richter *et al.*, 1997), the relationship between flow alteration features and river health still lacks a quantitative characterization (Jager and Smith, 2008). Consequently, simpler approaches like the one considered here are still the most widely used for regulatory purposes.

These operational restrictions limit the ability of the system to follow the pattern of energy prices and potentially reduce the economic value of daily generation. This effect can be alleviated if a water storage facility downstream of the power house re-regulates the release pattern (Richter and Thomas, 2006). Such an alternative typically exists in cascade hydropower systems, where the most downstream reservoir can be used for this purpose. In some systems, afterbays have been created for this purpose.

It is important to distinguish between re-regulation facilities whose sole purpose is to mitigate hydropeaking operations by an upstream reservoir, and those used for the double purpose of re-regulation and power generation. In the first case (Fig.3.1), which typically corresponds to a regulation facility at the downstream end of a hydropower reservoir system, all releases from the re-regulation facility are discharged into the stream. In this case, the re-regulation facility has to mitigate the hydropeaking operations and provide lower and upper bounds to instream flows.

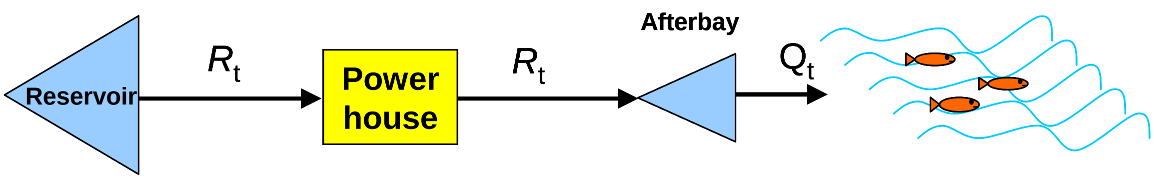


Figure 3.1: End-of-system afterbay schematics

In the second case, which will not be studied here, water releases from the re-regulation storage facility can be allocated either for power generation in a downstream plant or for instream flow in the downstream reach. Here, besides buffering ramping effects, the downstream facility ensures water is allocated to the stream at all times so the MIF requirement is met.

This chapter begins with the mathematical formulation of end-of-system afterbay operations as an optimization problem, a linear program. A model with hourly decisions is developed for a typical summer day in California. The behavior of solutions to this problem are then explored numerically and discussed in terms of hydropower and instream flow performance, afterbay capacity and operations, and turbine capacity.

3.2. Mathematical formulation

For daily operations on an hourly time-step, reservoir storage and elevation head can usually be considered fixed (for small rates of daily release relative to water stored and inflows for the immediately-upstream reservoir). Linear program formulations for maximizing the economic value of hydropower subject to capacity and minimum release and ramping constraints are developed for cases with and without an afterbay.

3.2.1 No afterbay

As a first step, the effects of minimum instream flow (MIF) and maximum ramping rate (MRR) requirements will be examined for a simple system, where hydropower releases are directly discharged into the stream.

The objective is to maximize the total daily value of hourly energy generation

$$Max \quad z = \sum_{t=1}^{24} p_t \cdot E_t \qquad (3.1)$$

Where p_t is the energy price and E_t is the energy generated at time t.

$$E_t = \eta \cdot \gamma \cdot h \cdot R_t \qquad (3.2)$$

Where η is the combined turbine and generation efficiency, γ is the specific weight of water, h is the (constant) water head, and R_t is the water release through the turbines at time t.

Hydropower operations are constrained by physical and regulatory restrictions. First, hydropower releases are bounded by turbine capacity.

$$R_t \le R_{MAX} \quad t = 1,...,24 \qquad (3.3)$$

The mass balance in the hydropower reservoir can be simplified at this time scale by defining a total daily target release volume. This eliminates the need to consider inflows to the reservoir. Therefore, the total daily hydropower release is constrained by the total daily release target:

$$\sum_{t=1}^{24} R_t \le R_{TOT} \qquad (3.4)$$

The regulatory constraints on stream releases are:

Minimum instream flow $\quad R_t \ge Q_{MIN} \qquad (3.5)$

Maximum up-ramping rate $\quad R_{t+1} - R_t \le \Delta Q^{UP} \qquad (3.6)$

Maximum down-ramping rate $\quad R_t - R_{t+1} \le \Delta Q^{DOWN} \qquad (3.7)$

This formulation can be summarized through the following linear program:

$$
\begin{aligned}
&\underset{R_t}{Max} \quad z = \sum_{t=1}^{24} p_t \cdot \eta \cdot \gamma \cdot h \cdot R_t \\
&s.t \quad R_t \le R_{MAX} \qquad t = 1,\ldots,24 \\
&\qquad \sum_{t=1}^{24} R_t \le R_{TOT} \\
&\qquad R_t \ge Q_{MIN} \qquad t = 1,\ldots,24 \\
&\qquad R_{t+1} - R_t \le \Delta Q^{UP} \qquad t = 1,\ldots,24 \\
&\qquad R_t - R_{t+1} \le \Delta Q^{DOWN} \qquad t = 1,\ldots,24 \\
&\qquad R_t \ge 0 \qquad t = 1,\ldots,24
\end{aligned}
$$

3.2.2 With afterbay (Re-regulation reservoir)

This formulation corresponds to the case of an end-of-system afterbay, whose sole purpose is to re-regulate the operations of an upstream hydropower reservoir. The problem is to operate both the hydropower reservoir and its re-regulation facility hourly to maximize total daily economic value of energy subject to constraints on the releases to the stream. A one-day time horizon is considered.

The operational decisions are the hourly releases from each storage facility (hydropower reservoir and afterbay) during the day.

The operational objective, turbine capacity constraint and daily water availability constraint are those of Eqs. (1.1) through (1.4).

The mass balance in the afterbay, neglecting evaporation for such short time periods, is:

$$S_{t+1} = S_t + (R_t - Q_t) \cdot \Delta t \qquad t = 1,\ldots,24 \qquad \Delta t = 3{,}600 \text{ sec} \tag{3.8}$$

Where S_t is the storage at the beginning of hour t and Q_t is the flow discharge from the afterbay during period t.

The following constraints (3.9a, 3.9b, 3.9c, and 3.9d) set storage bounds without imposing a timing phase or hour of minimum storage on the drawdown-refill cycle. First, initial storage is set as a large positive number: $S_1 = S_{ref}$ (3.9a)

Then define the maximum and minimum reference storages:

$S_t \ge S_{MIN}$ and $S_t \le S_{MAX}$ (3.9b)

Restrict storage range by afterbay reservoir capacity:

$$S_{MAX} - S_{MIN} \le S_{CAP} \tag{3.9c}$$

Real storages can be recovered by substracting the lower bound:

$$S_t^{REAL} = S_t - S_{MIN} \tag{3.9d}$$

To ensure temporal continuity in the problem, the final storage must be equal to the initial storage: $S_{24} + (R_{24} - Q_{24}) \cdot \Delta t = S_1$ (3.10)

The regulatory constraints on stream releases are now imposed on the releases from the afterbay:

Minimum instream flow $Q_t \geq Q_{MIN}$ (3.11)

Maximum up-ramping rate $Q_{t+1} - Q_t \leq \Delta Q^{UP}$ (3.12)

Maximum down-ramping rate $Q_t - Q_{t+1} \leq \Delta Q^{DOWN}$ (3.13)

The mathematical formulation of the problem is summarized in the following linear program:

$$
\begin{array}{lll}
\underset{R_t, Q_t}{Max} & z = \sum_{t=1}^{24} p_t \cdot \eta \cdot \gamma \cdot h \cdot R_t & \\
s.t & R_t \leq R_{MAX} & t = 1,...,24 \\
 & \sum_{t=1}^{24} R_t \leq R_{TOT} & \\
 & S_{t+1} = S_t + (R_t - Q_t) \cdot \Delta t & t = 1,...,24 \\
 & S_t \geq S_{MIN} & t = 1,...,24 \\
 & S_t \leq S_{MAX} & t = 1,...,24 \\
 & S_{MAX} - S_{MIN} \leq S_{CAP} & \\
 & S_1 = S_{ref} & \\
 & S_{24} + (R_{24} - Q_{24}) \cdot \Delta t = S_1 & \\
 & Q_t \geq Q_{MIN} & t = 1,...,24 \\
 & Q_{t+1} - Q_t \leq \Delta Q^{UP} & t = 1,...,24 \\
 & Q_t - Q_{t+1} \leq \Delta Q^{DOWN} & t = 1,...,24 \\
 & R_t \geq 0, \quad Q_t \geq 0 & t = 1,...,24
\end{array}
$$

3.3 Model parameters

Model parameters define infrastructure and instream flow regulatory constraints, daily hydropower release targets, and energy prices. Turbine capacity (R_{MAX}) was set at 50 m3/s. Afterbay storage capacity (S_{MAX}) values of 180,000 m^3 and 360,000 m^3 will be modeled, besides the No Afterbay case. These capacities are equivalent to a continuous flow of 50 m3/s (turbine capacity) during one and two hours, respectively. Other fixed parameters are: $h = 100\ m$, $\eta =$ 0.80, and $\gamma = 9.8\ kN/m^3$. Hourly energy prices p_t are based on average August 2005 for the California ISO system (Fig.3.2). In general, higher energy prices are between noon and midnight. The lowest prices are between 3 AM and 8 AM. Ordinal numbers on top of each column represent the rank of each hour in order of decreasing price.

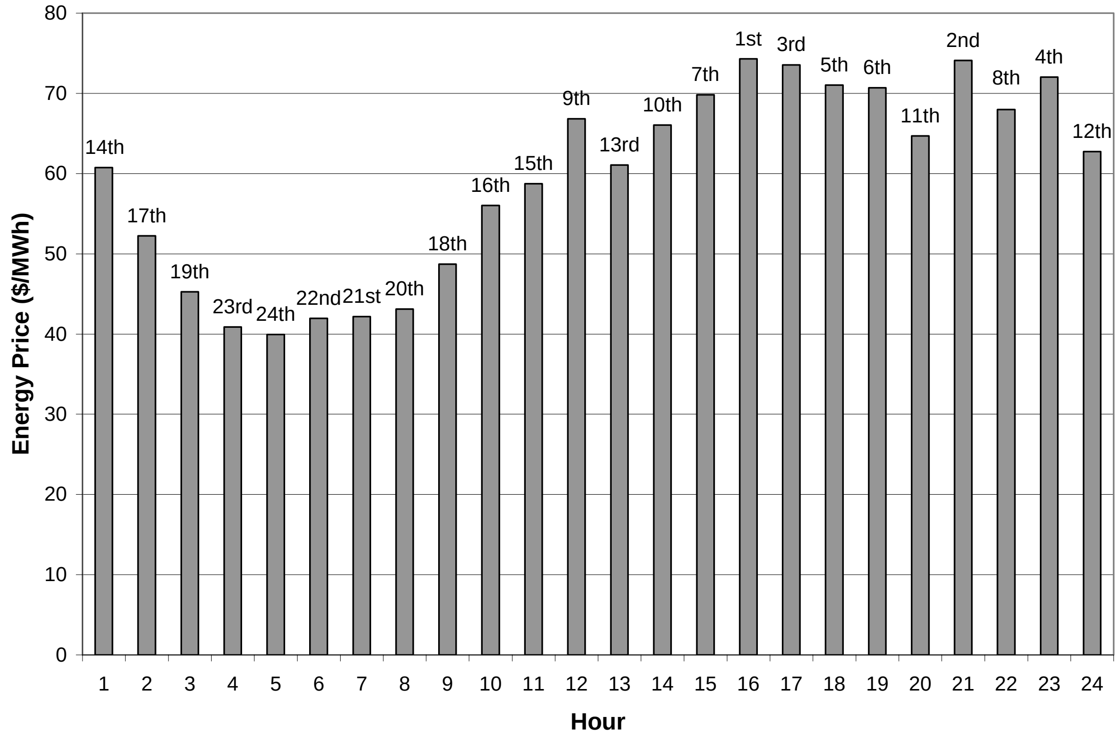


Figure 3.2: Hourly energy price August 2005 (Source: Cal-ISO)

Values of regulatory-constraint parameters and daily hydropower release targets originate from various policy scenarios for hydropower operations. These scenarios are described in the next section.

3.4 Regulatory scenarios

Different regulatory scenarios can be explored by changing the parameters Q_{MIN}, ΔQ^{UP}, and ΔQ^{DOWN}. The two ramping parameters will be assumed equal for ease of analysis and lack of evidence of its relative effect on the downstream ecosystem. Daily operational scenarios can be defined through different daily hydropower release targets, R_{TOT}. Ranges for these parameters can be defined based on the fixed turbine capacity, R_{MAX}, through the following inequalities.

Total daily hydropower release must be within the range defined by turbine capacity times hours of the day: $0 \le R_{TOT} \le 24 \cdot R_{MAX}$.

Minimum instream flow must be within the range defined by the average hourly release target: $0 \le Q_{MIN} \le R_{TOT} / 24$.

Ramping rates ranges are defined by the difference between turbine capacity and minimum flow: $0 \le \Delta Q^{UP} \le R_{MAX} - Q_{MIN}$ and $0 \le \Delta Q^{DOWN} \le R_{MAX} - Q_{MIN}$.

3.5 Model results

The results of the optimization models under different scenarios allow for analysis of several economic and operational aspects of the system. The effects of regulatory policies (i.e., instream flow constraints) on hydropower revenues and on how the system is operated are examined. Operational results include the optimal daily pattern of hydropower releases and releases to the stream. The economic value of expanding turbine capacities under each scenario also is of interest.

3.5.1 Effects of instream flow constraints on hydropower revenues

The unconstrained case defines a base for comparison. Figure 3.3 shows the optimal revenue for the relevant range of total daily hydropower releases, with no constraints on releases to the stream. The curves are identical, therefore undistinguishable, for all three afterbay storage capacities (including the No Afterbay case). Expectably, a re-regulation facility has no economic value if hydropower operations are not constrained by instream flow restrictions. The daily revenue the system can generate when it operates at full capacity the entire day is about \$56,000. The revenue from increasing daily release is somewhat non-linear, with preference given to maximizing release during hours when energy prices are highest. With limited turbine capacities, larger daily release target volumes force larger releases during off-peak times, when energy prices are lower. The marginal revenue (slope of the curve) therefore decreases as larger mounts of water are available.

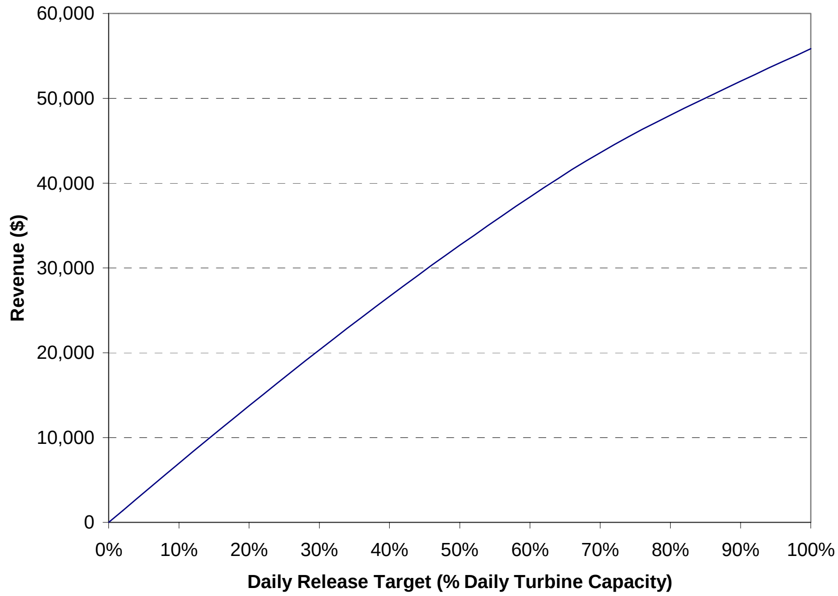


Figure 3.3: Optimal daily hydropower revenues with unrestricted instream flow

The effects of varying minimum instream flow (MIF) levels with no ramping constraints are shown in Fig. 3.4, for the afterbay storage capacity of zero, and storage capacities equivalent to one and two hours of operation at turbine capacity, respectively. Series represent daily hydropower release target as a percentage of the maximum usable level, defined 24 hours operating at turbine capacity. For all three storage capacities revenues decrease as the MIF requirement increases. However, the effect is clearly milder as storage capacity increases. For example, for a daily release target set to 50% of maximum daily release, with no afterbay the revenue decreases from $32,685 to $27,923, equivalent to 15%. With an afterbay, revenues fall to $29,614 and $30,743, equivalent to 9% and 6%, for the smaller and bigger capacity, respectively. The reductions in revenue losses—$1,691 and $2,820 for the smaller and larger, respectively in this example—represent the economic value of afterbays for the system. Another interesting observation is that the slope of each curve tends to become more negative as the MIF requirement increases. In other words, the marginal decrease in revenues increases with the minimum flow requirement. This can be explained by the fact that as the MIF increases, more of the available water is spent during hours with low energy price.

The effects of ramping constraints on revenues are shown in Fig. 3.5. Each curve represents a daily hydropower release target as a percentage of the level defined by 24 hours operating at turbine capacity, and afterbay capacity levels. As the maximum allowed ramping rate increases, operations are less constrained and therefore revenues increase, eventually reaching unconstrained levels. The reduction in revenues due to restricted ramping is greater for the case with no afterbay. For a daily hydropower release target of 50% of total capacity, a 17% reduction in daily revenue occurs between the unconstrained and zero ramping case. The reduction is 10% and 6% for afterbay storage capacity equivalent to one and two hours operating at turbine capacity, respectively.

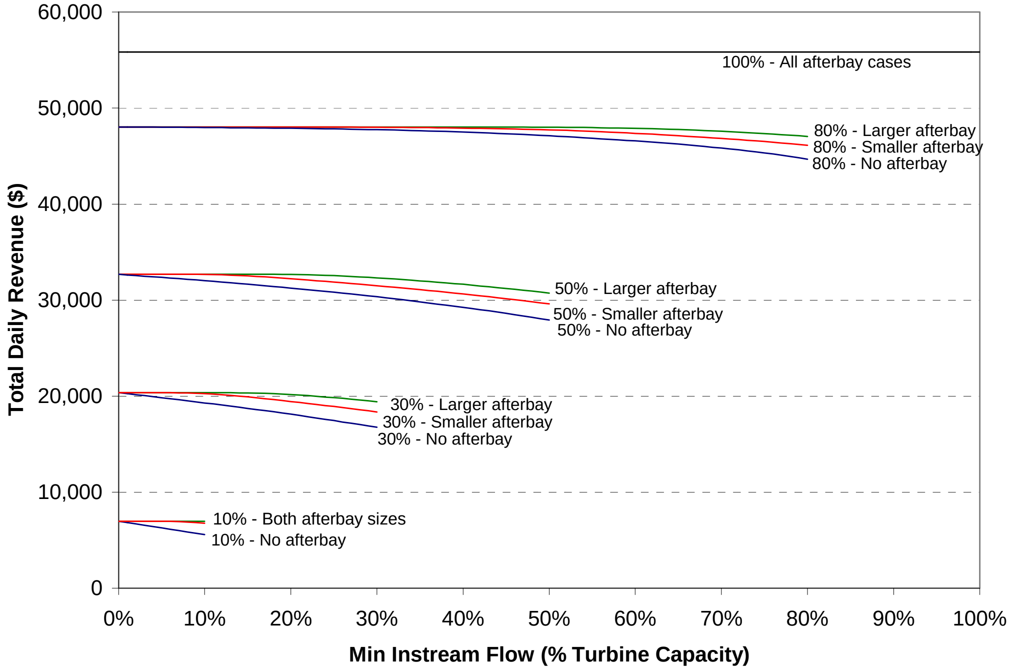


Figure 3.4: Effect of MIF on daily revenues for different levels of daily release and afterbay size

The effect of ramping constraints on revenue is strongest for intermediate daily water availability levels. Ramping rate constraints have little effect when very little or very much water is available for the day. For those curves where revenues are affected by ramping constraint levels, the marginal effect of limiting ramping rates decreases as higher ramping rates are allowed. Thus, the reduction in revenues due to ramping constraints is steepest for relatively small ramping rates. When higher ramping rates are allowed, the revenue approaches rapidly that of the unconstrained case. The range of ramping rates affecting the revenues is influenced by the existence and size of the re-regulation reservoir. Without re-regulation, revenues are affected within a wide range of allowed ramping rates. The unconstrained revenue levels are reached only for ramping rates beyond 90% of turbine capacity per hour. Afterbay capacity limits the range of ramping rates which affect revenues. For an afterbay able to store an hour of operation at turbine capacity, revenues are only affected when allowed ramping rates are below 15% of turbine capacity per hour. This range decreases to 10% for an afterbay twice as large. This is the range where a conflict exists between the goals of avoiding sudden streamflow fluctuations and maximizing hydropower revenues. Restrictions outside this range will not affect revenues. Identifying this range is important for FERC licensing negotiations.

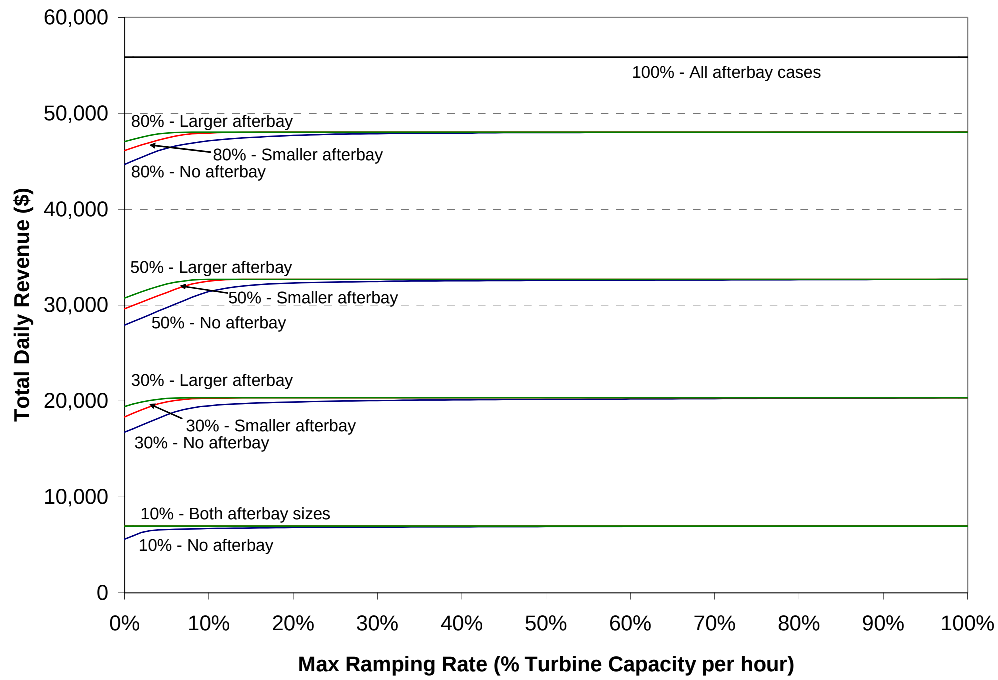


Figure 3.5: Effects of ramping constraints on daily revenue for different levels of daily release and afterbay size

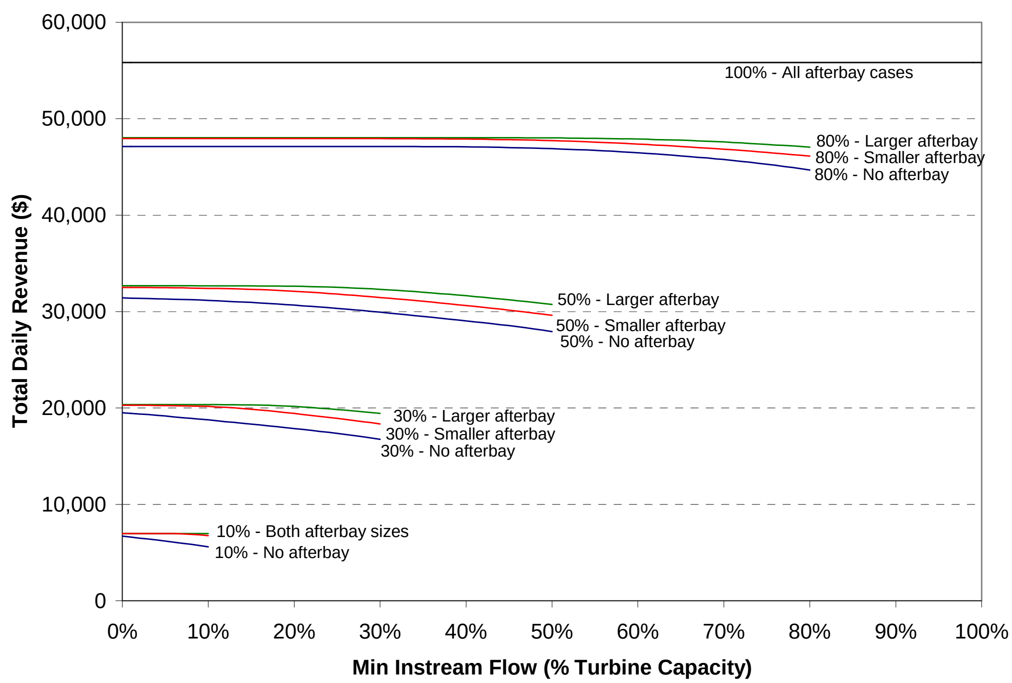


Figure 3.6: Combined effect of MIF and ramping constraints on revenues with maximum ramping rate of 10% of turbine capacity

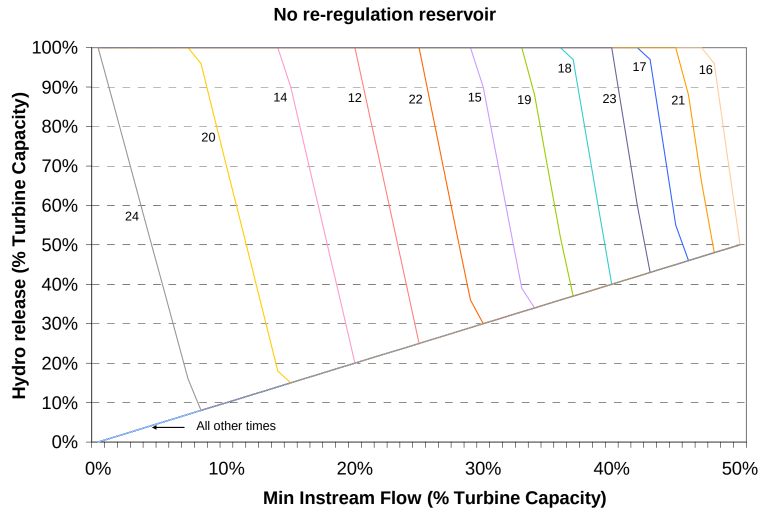
The combined effect of minimum flow and ramping constraints on hydropower revenues is show in Fig. 3.6. The graph shows how the optimal daily revenue changes for different levels of minimum release to the stream, when ramping rates are restricted to be less than 10% the turbine capacity per hour. The effect is similar to that observed in Fig.

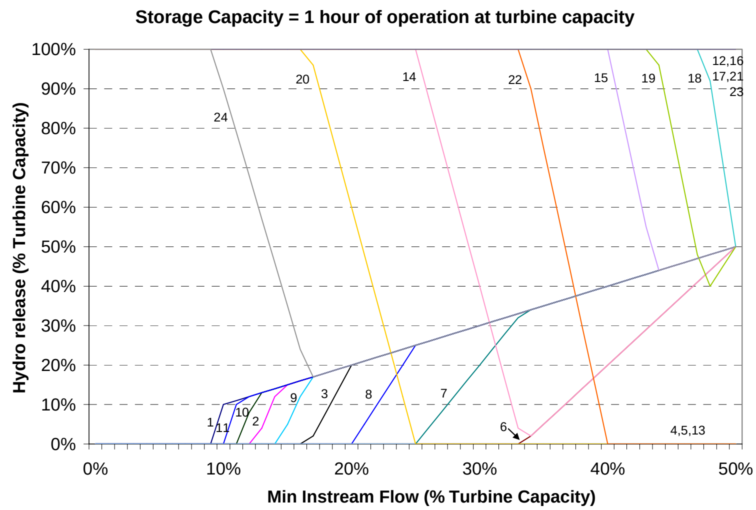
3.4, although in this case the curves without an afterbay are further apart from those with afterbay, in particular for low MIF requirements. This is due to the additional effect of the MRR. This situation, with relatively low MIFs (compared with turbine capacity) and relatively stringent ramping rates, will likely be encountered during FERC licensing negotiations for hydropower systems in the California Sierra Nevada. Without an afterbay, revenue levels are lower for all daily hydropower release target (series) and for small required instream flow. As the MIF increases, the revenue becomes closer to (even coincides with) that with MIF but unconstrained ramping. So, when large MIFs are required, ramping rates can be as stringent as 10% of turbine capacity per hour, without additional effect on revenues. This is reasonable, since increasing MIFs reduces the range of physically possible ramping rates, as seen in the ranges defined in Section 3.4. With a re-regulation reservoir, the curves practically coincide with those obtained when ramping is unconstrained. In this case, limiting ramping rates to 10% of the turbine capacity per hour has no additional effect on revenues to that attributed to minimum required releases to the stream. Again, the existence of an optimally operated afterbay reduces the degree of conflict between hydropower generation and instream flow goals.

3.5.2 Hydropower generation pattern

Daily hydropower generation is expected to follow the pattern of energy prices. Thus, in the unconstrained case, the water available for the entire day would be allocated for generation when energy is most valuable, and then allocated to less valuable hours as turbine capacity is reached. This would continue until the day’s allocation of water to release was exhausted, leaving no discharge in any remaining off-peak hours. MIF and ramping rate constraints reduce the flexibility of the system to allocate water this way. If no re-regulation reservoir is available, such constraints are imposed directly on the hydropower generation pattern. In this case, releases to the stream coincide in magnitude and timing with those of hydropower generation. All the results shown in this section are for a daily hydropower release target equal to 50% the maximum usable daily water volume, as defined by turbine discharge capacity. In other words, the daily release target is enough to operate during 12 hours (50% of the day) at turbine capacity, although the actual allocation can consider intermediate releases (less than capacity) during some hours.

Fig. 3.7 shows the effect of a MIF requirement on the hydropower release pattern. Each series represents an hour during the day. For the case without an afterbay (top graph), under no minimum flow requirement the hydropower release equals turbine capacity for twelve hours in the day (those when energy price is highest) and zero for those hours when energy is least valuable. This is expected, since the daily hydropower release equals 50% of the maximum volume defined by turbine capacity. As the required release to the stream increases, hydropower releases during less valuable hours make up the required MIF and, since only a fixed amount of water is available for the day, hydrogeneration decreases during some of the more valuable hours (in order of increasing energy price). The MIF is first allocated to every hour in the day and the remaining water, if any, is allocated is order of decreasing energy price. When the MIF matches the average hourly water availability (50% of turbine capacity in this case), hydropower releases are steady all day.





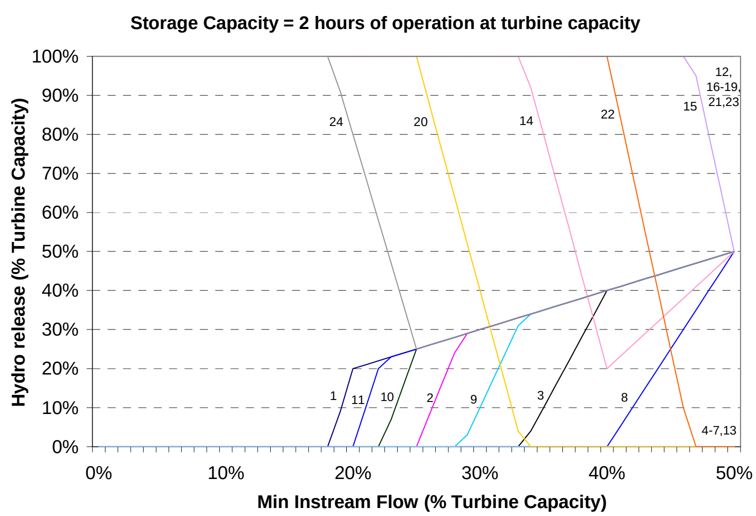


Figure 3.7: Hydropower release pattern under MIF for daily hydropower release of 50% of maximum

With an afterbay, the unconstrained hydropower release pattern, i.e. generation at turbine capacity during the twelve more valuable hours and zero during the rest of the day, is observed when relatively small instream flows are required. For instream flow requirement up to 9% of turbine capacity, hourly hydropower generation releases are the same as if no minimum release to the stream was imposed. This MIF level up to which revenues are not affected increases to about 18% for an afterbay twice as large. Beyond this range, generation gradually increases during the off-peak hours and decreases during the peak hours. With re-regulation storage capacity, even when MIF is the highest possible, hydropower releases are uneven during the day, with some (most valuable) hours generating at turbine capacity, and no generation at times when energy prices are lowest. Interestingly, hydropower releases during hours 20 and 22 go from turbine capacity to zero as the MIF requirement increases. Also, releases during hour 12 remain at turbine capacity for all MIF levels, whereas generation during hours with higher energy prices is less than capacity starting at some MIF levels. With re-regulation, the operational pattern departs from the simple one described for the case without an afterbay. Hydropower releases can be less than the MIF, and water is not necessarily allocated in order of decreasing price. The sequence of hydropower releases is such that the MIF can be released by the afterbay, which has a limited regulation capacity, at all times. In this case, the sequence of energy prices plays role as it will be clear from the daily sequence of afterbay storage. From Fig. 3.2, it is clear that prices in hours 20 and 22 share a unique feature. Those are both hours of relatively high energy prices, but are preceded and followed by higher prices. On the contrary, hour 12 is between two hours when energy price is smaller.

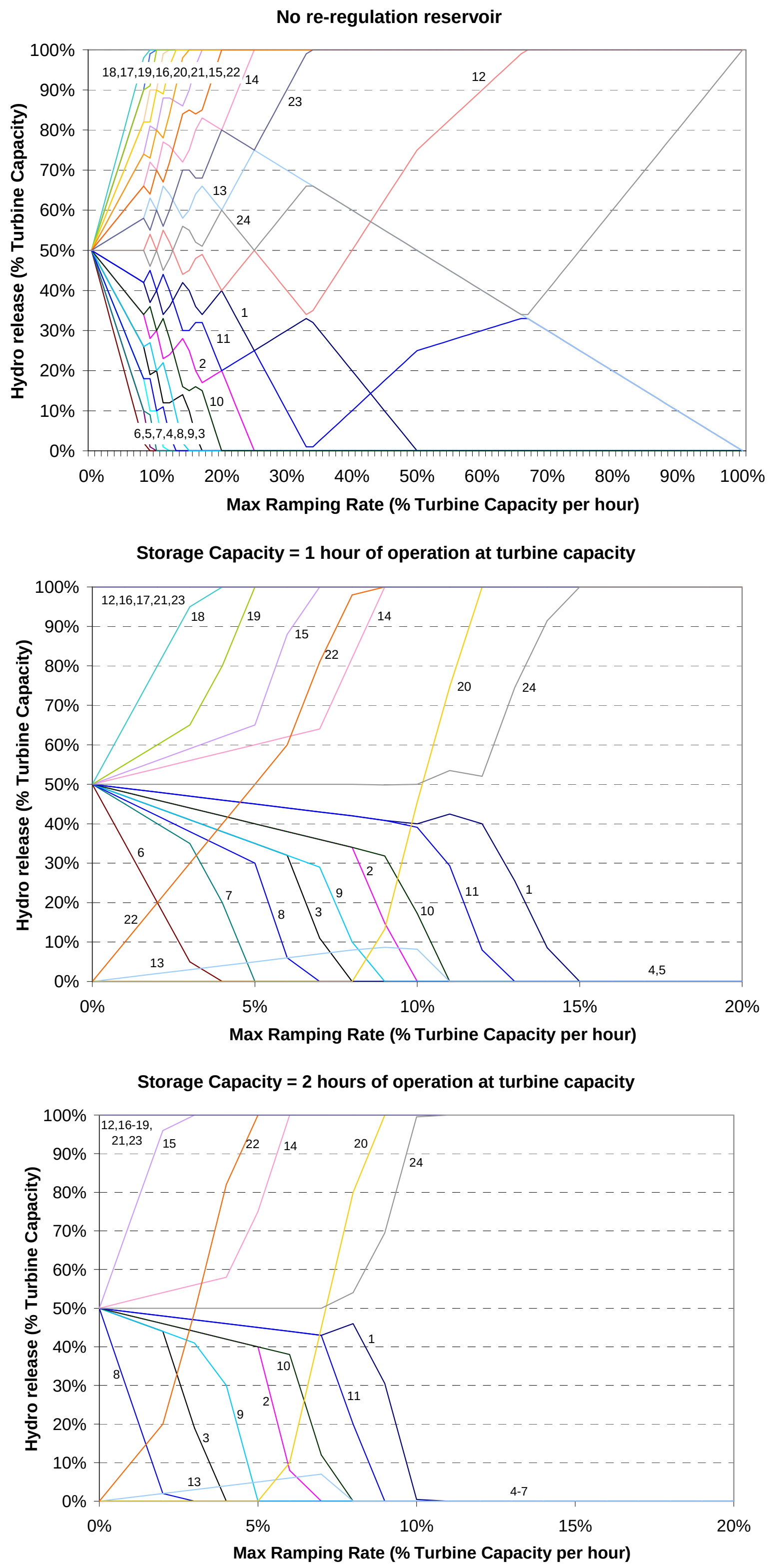


Figure 3.8: Hydropower release under ramping constraints for daily hydropower release of 50% of maximum

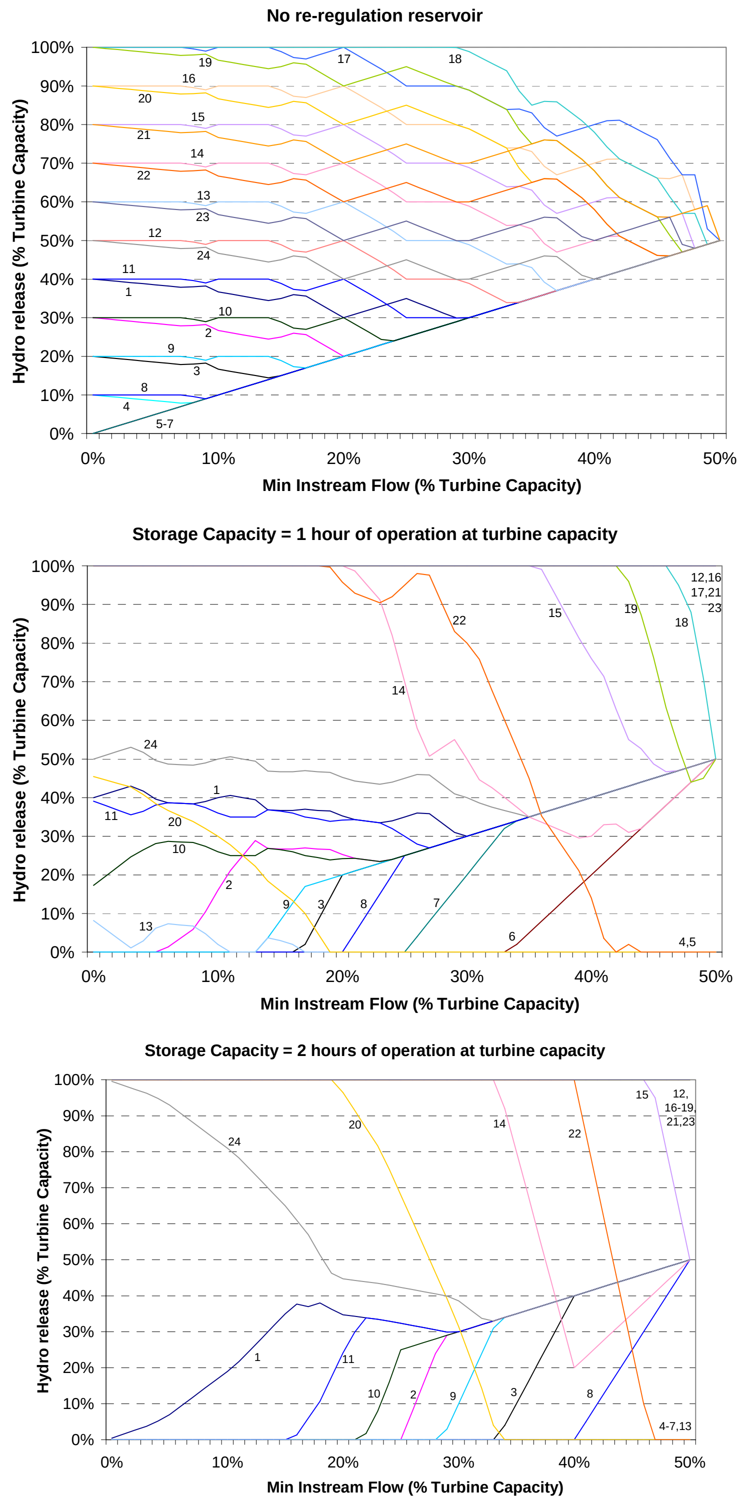


Figure 3.9: Hydropower release under combined constraints for ramping rate 10% of turbine capacity and daily hydropower release of 50% of maximum

The effect of ramping constraints on hydropower releases is shown in Fig. 3.8. Without an afterbay, hydropower releases are steady and unchanging if no ramping is allowed. As allowable ramping rates are increased, releases tend to increase during the most valuable hours and decrease when energy is cheapest, as expected. The oscillation observed in the releases can be attributed to the small fluctuations observed in energy prices during peak times. Unlike the case of MIF alone, the effect of ramping rate constraints depends on the timing of prices. A similar behavior is observed when hydropower releases can be re-regulated by an afterbay. However, as the ramping constraint's effects are dampened or eliminated, releases reach the optimal unconstrained zero-100% pattern (twelve hours operating at capacity and the other twelve with no generation), even with more stringent MRRs. This optimal pattern can be achieved with ramping rates greater than 18% and 12%, for the smaller and larger afterbay, respectively. Constrained ramping affects the revenue only for smaller allowable ramping rates. Similar to what was observed for MIFs, releases during hours 20 and 22 can vary from zero to turbine capacity as the restriction becomes less stringent, in this case as allowed ramping rates increase. This can be explained because under ramping constraints, release at a given hours constrains the releases in the previous and next hours. Since energy prices are very high in hours 19, 21, and 23, releases in hours 20 and 22 must be sufficiently high to allow operation at turbine capacity during hours when energy is very valuable.

The combined effect of minimum flow and ramping constraints on hydropower release decisions is shown in Fig. 3.9, for a MRR of 10% of turbine capacity per hour. Without re-regulation, the MRR eliminates the possibility of zero-100% generation releases. Even if no minimum flow is required, hydropower releases cover the entire spectrum (from zero to 100%), with increases of 10% of turbine capacity (allowed MRR) between hours. This is in contrast with the corresponding result in Figure 7, where the zero-100% release pattern was observed when no MIF was required. Of course, more water is released during hours of high energy price. When releases are re-regulated through an afterbay, for low MIFs the system operates at full capacity during some hours, at intermediate levels during others, and not at all at other times. For an afterbay twice as large, the hydropower releases follow a pattern closer to that with unconstrained ramping. If no minimum flow is required, the zero-100% pattern is observed. For relatively high required releases to the stream, the patterns observed in this case almost coincide with those observed in Fig. 3.7, without a ramping constraint.

3.5.3 Instream flow pattern

The instream flow pattern is important for the ecosystem (Moog, 1993). This section presents the time series of releases to the stream for a daily hydropower release target of 50% the maximum usable water defined by turbine capacity. Fig. 3.10 shows the sequence for MIF requirements between 0% and 50% (maximum feasible in this case) and unconstrained ramping. With no afterbay (top graph), releases to the stream coincide with hydropower releases and therefore are constrained by turbine capacity. Only the minimum releases occur during the 11 PM to 11 AM off-peak period. During the rest of the day, water is allocated to the hourly periods when water is more valuable, within the total daily release volume. For example, with no minimum required release, releases to the stream are zero during hours 1-11, and 13. Releases are equal to turbine capacity during all other times. If the MIF requirement increases to 10% of turbine capacity, releases to the stream are equal to the turbine capacity during hours 12, 14-19, and 21-23. Only the minimum is released during hour 24 whereas during hour 20 only 70% of turbine capacity is discharged to the stream. For a required minimum flow equal to 50%

turbine capacity (the same as our daily release volume), the same flow is released to the stream during the entire day. A similar pattern occurs with releases to the stream from an afterbay. However, during the peak period strong hourly fluctuations are observed, which can be explained by the lesser peaks in energy prices. The peak instream flows during the peak period reach values of twice the turbine capacity for small MIFs, probably to ensure the afterbay empties before the next day's peak period. This behavior is interesting, since the existence of low minimum flow constraints with no restriction on ramping rates seem to cause these high releases to the stream in presence of an afterbay. Besides, the highest peaks occur for cases when low or no MIF is required. Maximum releases to the stream were not imposed in the original version of the model.

The effects of ramping constraints with no MIF on the hourly instream release pattern are presented in Fig. 3.11. Without an afterbay, releases to the stream are those of hydro-generation. Except when no ramping is allowed, releases to the stream tend to be small (even zero) during the night and morning, and high during the afternoon and evening, when turbine capacity is reached. For allowed ramping rates up to 40% of turbine capacity per hour, releases to the stream are zero somewhere during the off-peak period, and tend to reach turbine capacity during on-peak hours, with a linear behavior in between. When ramping beyond 50% of turbine capacity is allowed, a peak streamflow is observed at noon. This can be explained due to the very high price of energy between 11 AM and noon, compared to its preceding and following hours. Under constrained ramping, the sequence of price matters. With an afterbay, a similar pattern is observed for off-peak hours. However, considerably more fluctuations than without an afterbay (although within the acceptable ramping ranges) are observed during the on-peak period. Instream flows reach 200% of turbine capacity when generation is most valuable. Once again, it seems that when the unconstrained case is approached, large releases to the stream are induced. As with MIF requirement, the highest peaks occur when the restriction is less stringent.

Fig. 3.12 shows the pattern of releases to the stream for a combination of MIFs and a maximum ramping rate of 10% the turbine capacity per hour. In this case, a similar pattern is observed for all three afterbay sizes. In general, the instream flow equals the minimum requirement during off-peak hours, and it reaches about turbine capacity during the on-peak period. As the required release to the stream increases, the maximum released observed during on-peak hours decreases, because only a finite amount of water can be released in total during the day. Interestingly, unlike the case without ramping constraints (Fig.3.10) releases to the stream barely exceed turbine capacity during on-peak hours. Imposing a restriction on ramping also limits the maximum flows releases to the stream. These results show that combinations of MIF and MRR restrictions can induce very regular patterns of releases to the stream.

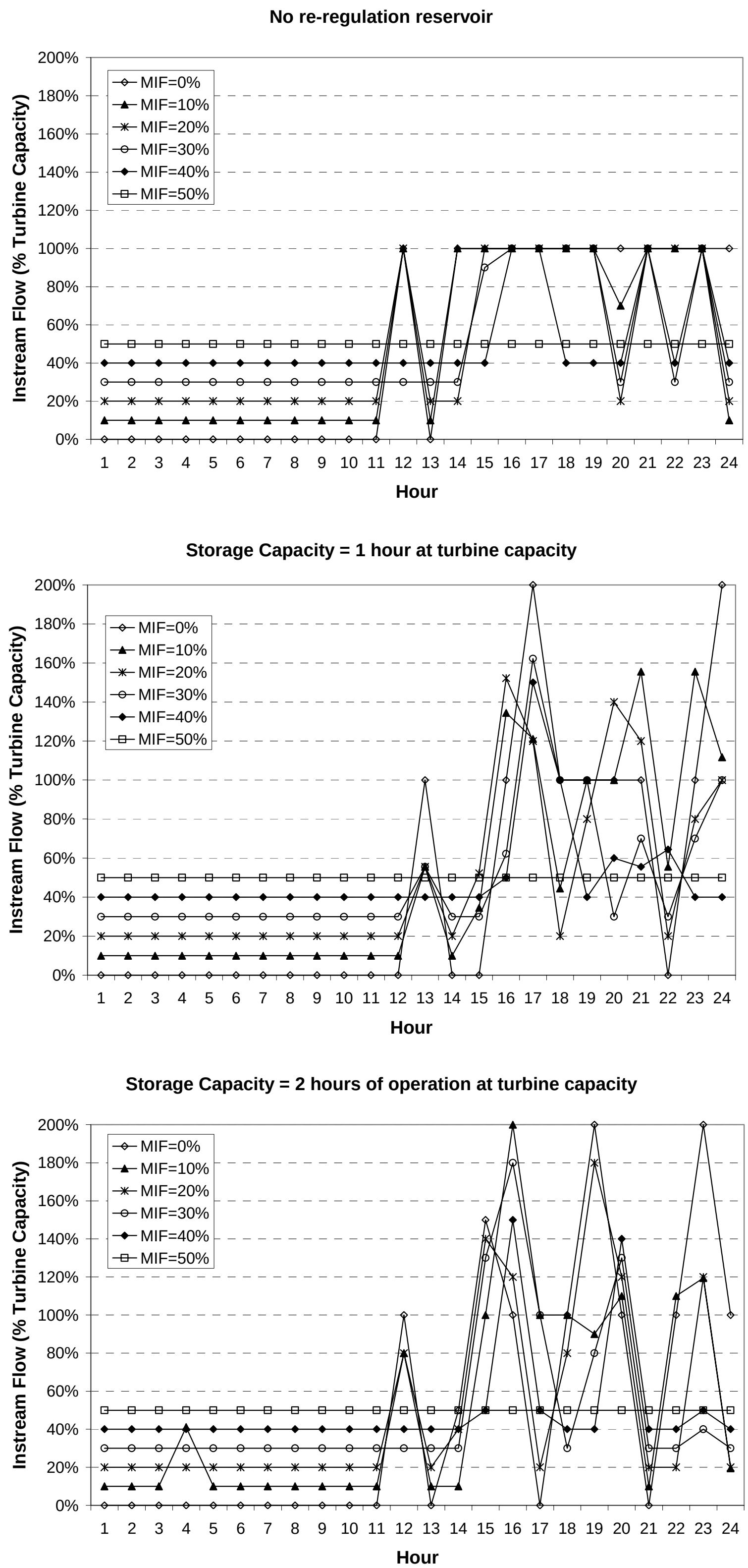


Figure 3.10: Instream flow hourly pattern under different levels of MIF

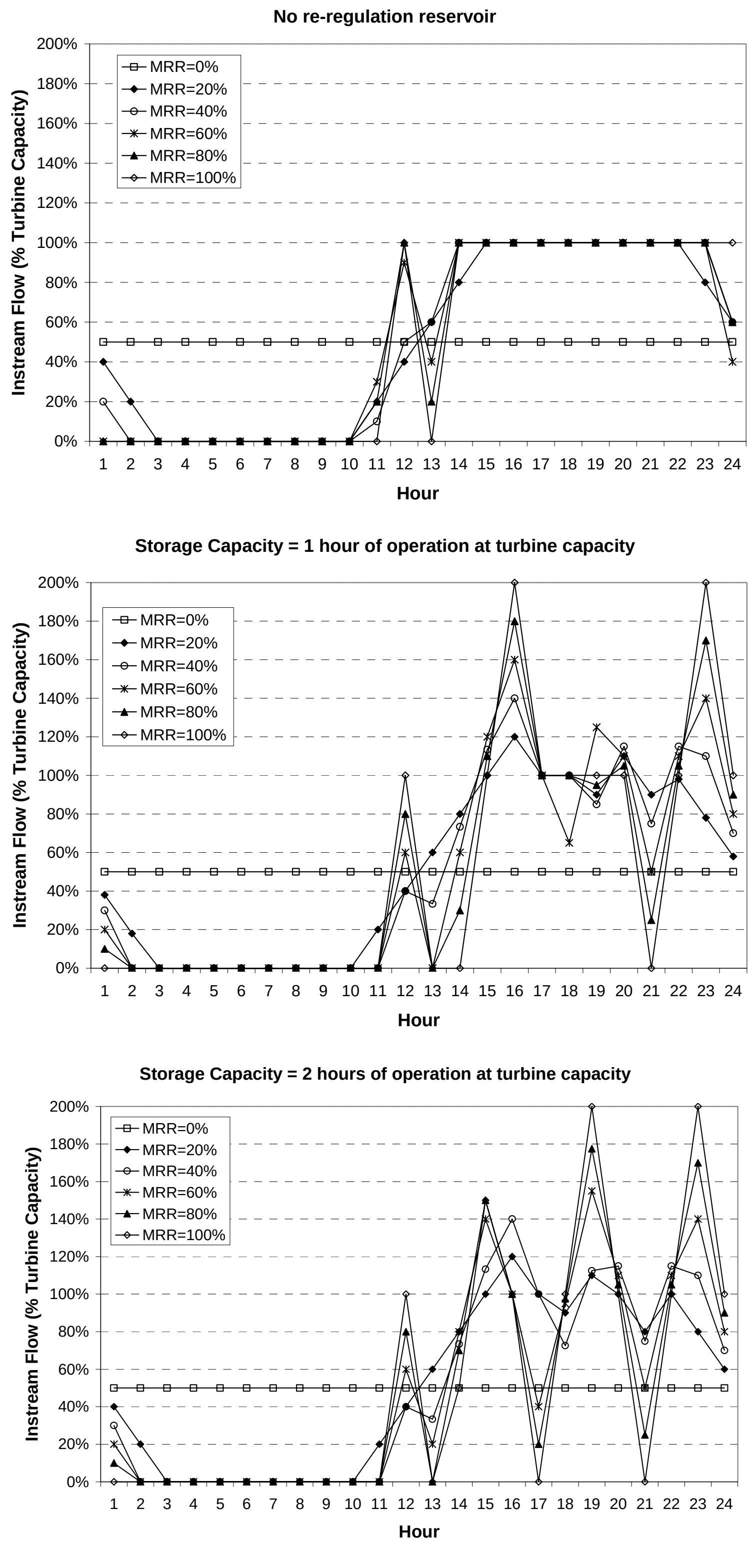


Figure 3.11: Instream flow hourly pattern under different levels of ramping rates

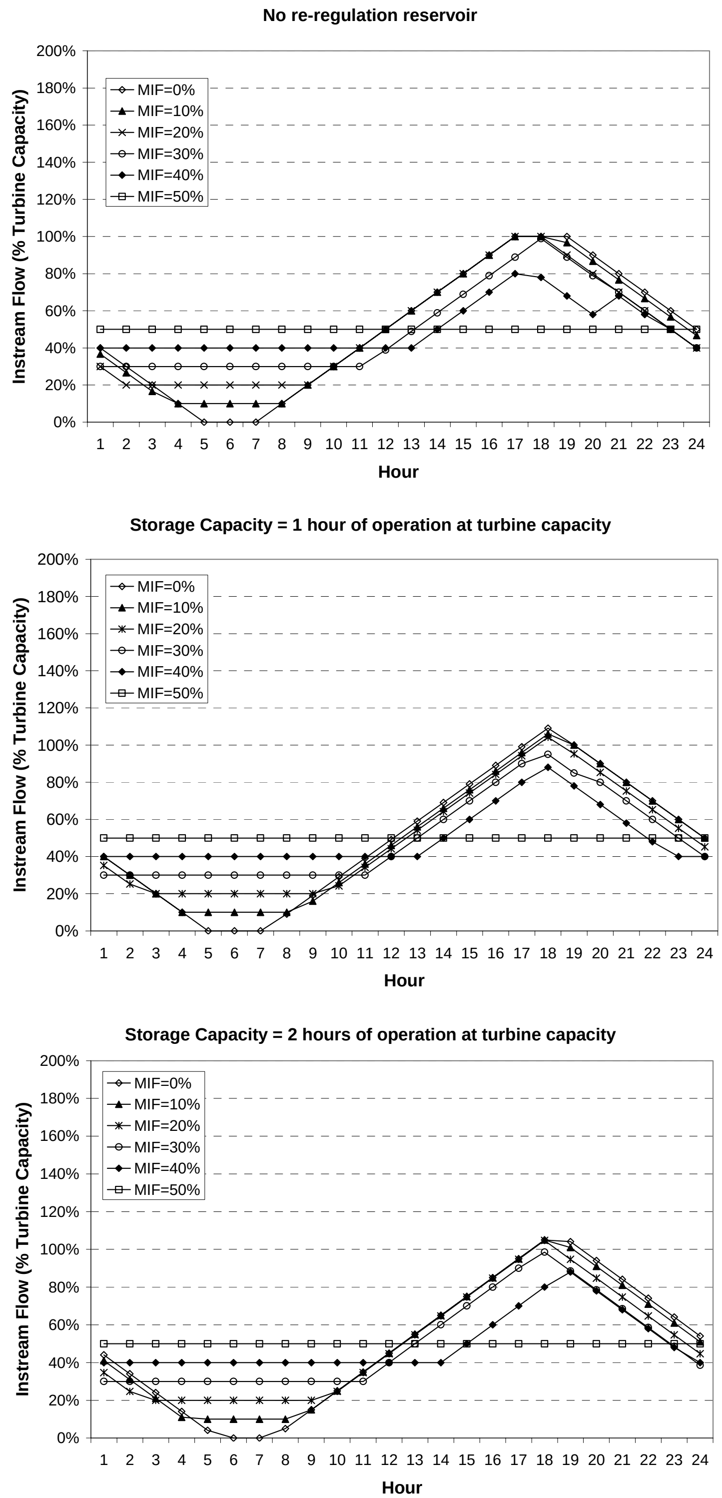


Figure 3.12: Instream flow hourly pattern under combined constraints

The very high instream flows observed with afterbays when imposing MIF or MRR alone seem counterintuitive. The existence of an afterbay optimally operated should result in better instream flow patterns than those obtained without re-regulation. Moreover, the flow pattern obtained without re-regulation is always feasible with an afterbay in place. Evidently, the problem is caused by the fact that instream flows are only controlled by constraints, but they play no role on the objective function. Therefore, there exist numerous alternative patterns of releases to the stream that will result in the same hydropower revenue, including the pattern obtained without an afterbay. In other words, among those instream flow patterns meeting all the constraints, including MIF and MRR, more desirable solutions can be found without affecting the level of revenues. To probe this point, the formulation was slightly modified by introducing persuasion penalties on undesirable outcomes in the objective function, i.e. subtracting small penalties from the total hydropower revenue so that instream flow releases are forced to take the more desirable values among all possible feasible combinations. Penalties were applied on the maximum instream flow observed in the day, and on the total magnitude of daily fluctuations, expressed as the sum of all hour-to-hour fluctuations (in absolute value). This approach to finding alternate optima is based on a similar procedure suggested by Revelle (1999).

Alternative instream flow patterns under MIF alone with the smaller afterbay are shown in Fig. 3.13. The sequences in the top graph were obtained by imposing a penalty of total daily fluctuations. The center graph shows instream flow sequences obtained when the maximum release to the stream is penalized. Results obtained for a combination of both penalties are shown in the bottom graph. The penalties did not affect the optimal daily revenue or hydropower releases and constitute alternate optima with the original formulation. All the flow patterns in Fig 3.13 are alternative to those in the center graph of Fig. 3.10. Much more regular patterns are observed with the introduction of persuasion penalties. With a penalty on the maximum release, turbine capacity is never exceeded during the day. The decision regarding which of these instream flow patterns is more desirable for the downstream ecosystem can be solved in practice during the negotiations considered within the licensing process for hydropower plants. More scientific knowledge is still required for a conclusive answer when faced to this choice (Jager and Smith, 2008).

Similarly, Fig. 3.14 includes three alternative patterns of releases to the stream with the larger afterbay under MIF constraints. Again, much more regular patterns than those observed in the bottom graph of Fig. 3.10 were identified. Patterns are very similar to those observed with the smaller afterbay (Fig. 3.13).

The alternative flow patterns under MRR constraints are presented in Figs. 3.15 and 3.16, for the smaller and larger afterbay, respectively. When contrasted with the results in the center and bottom graphs in Fig. 3.11, differences are evident. Expectably, more regular patterns are observed when fluctuations are penalized. Releases to the stream do not exceed turbine capacity when a penalty on the maximum daily release is introduced. With the larger afterbay, the instream flow patterns obtained with penalized maximum release and combined penalty are identical.

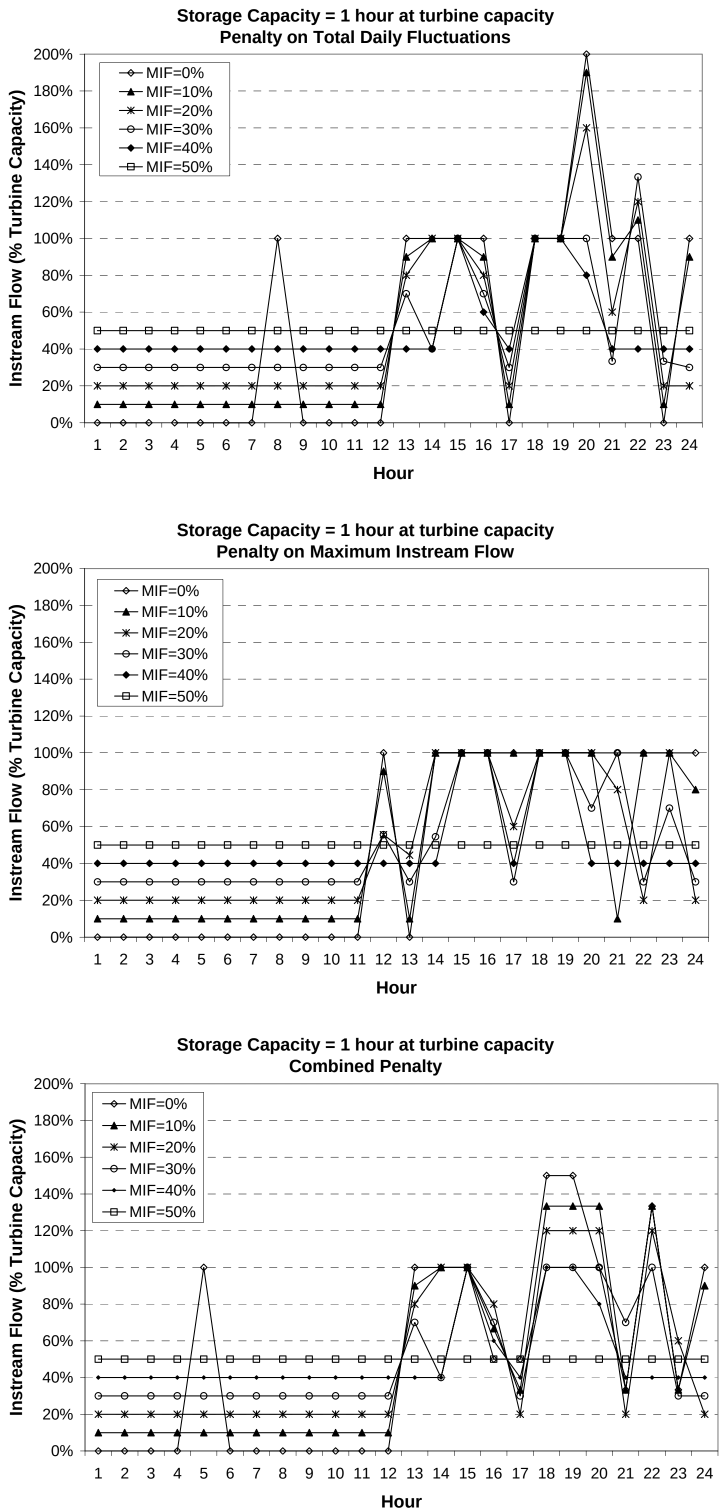


Figure 3.13: Alternative instream flow patterns for smaller afterbay under MIF

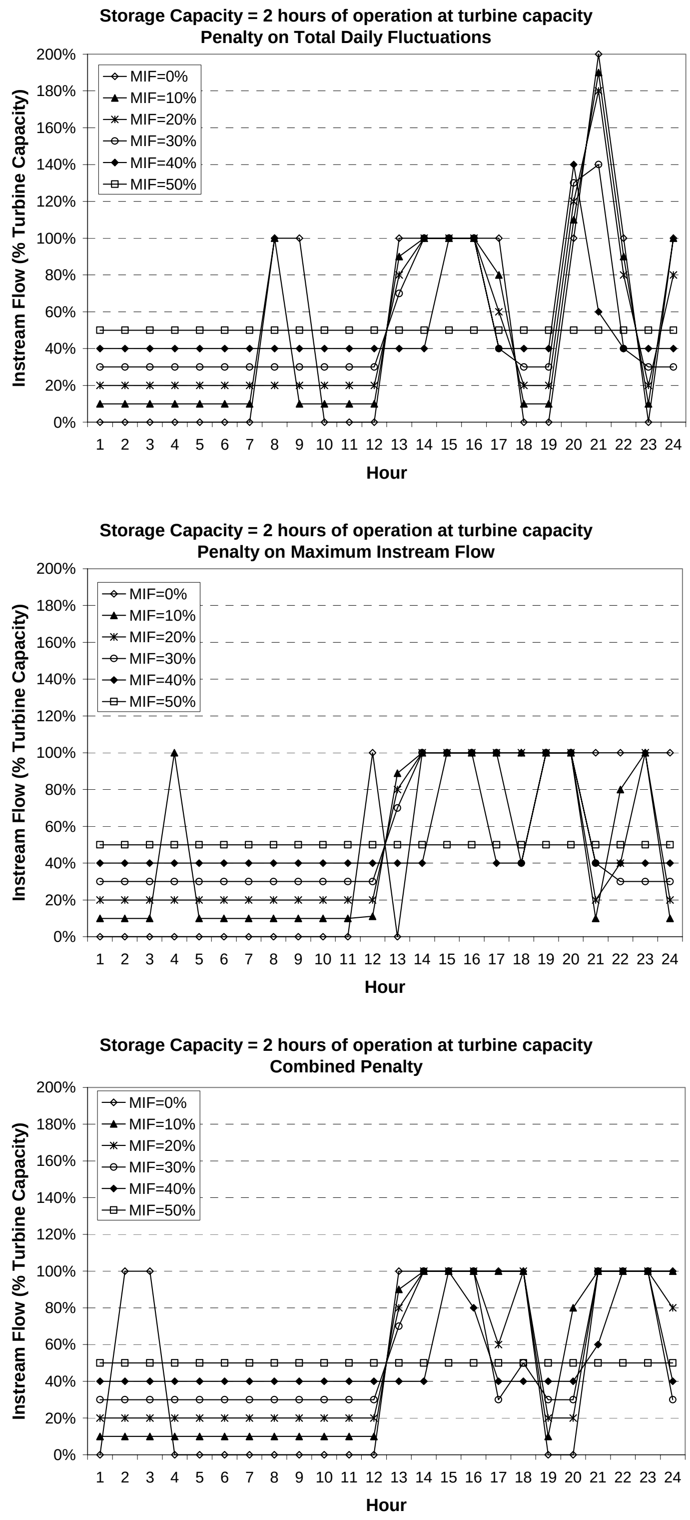
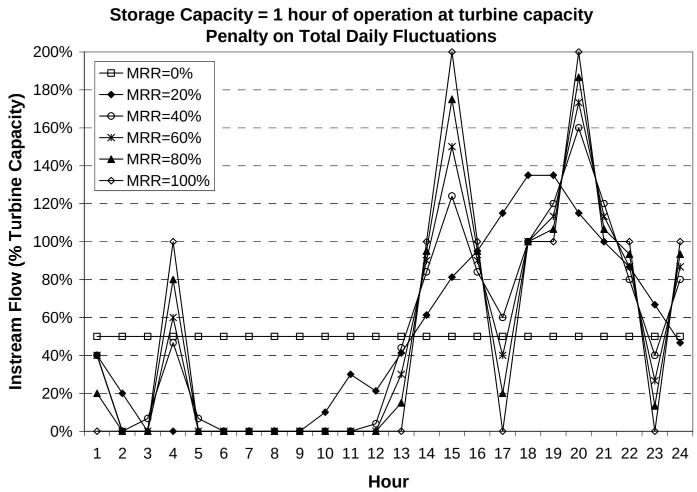
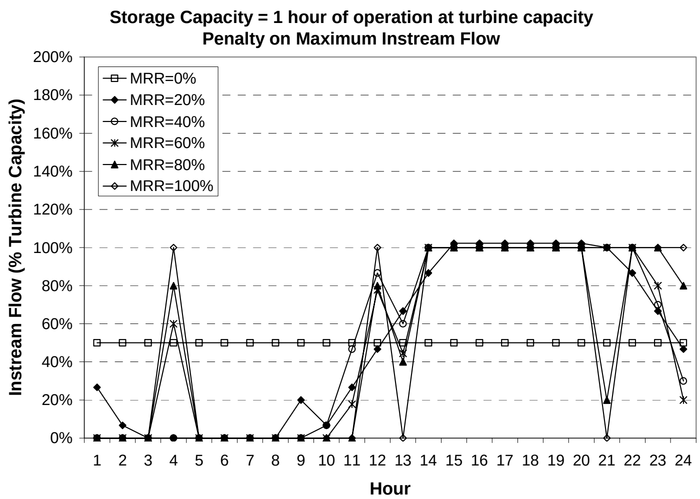


Figure 3.14: Alternative instream flow patterns with larger afterbay under MIF





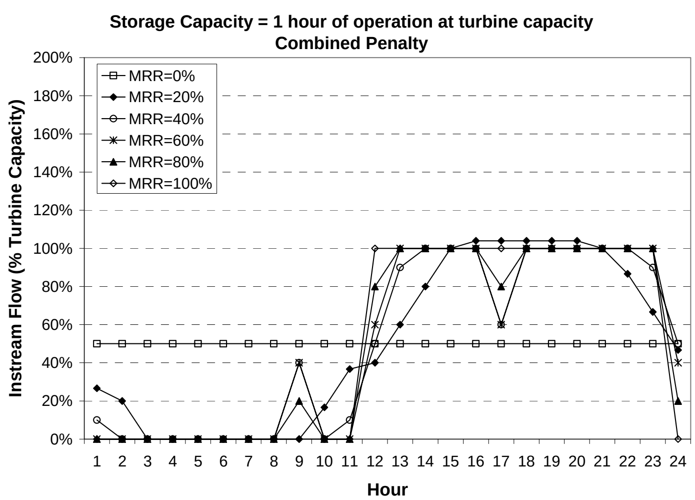


Figure 3.15: Alternative instream flow patterns with smaller afterbay under MRR

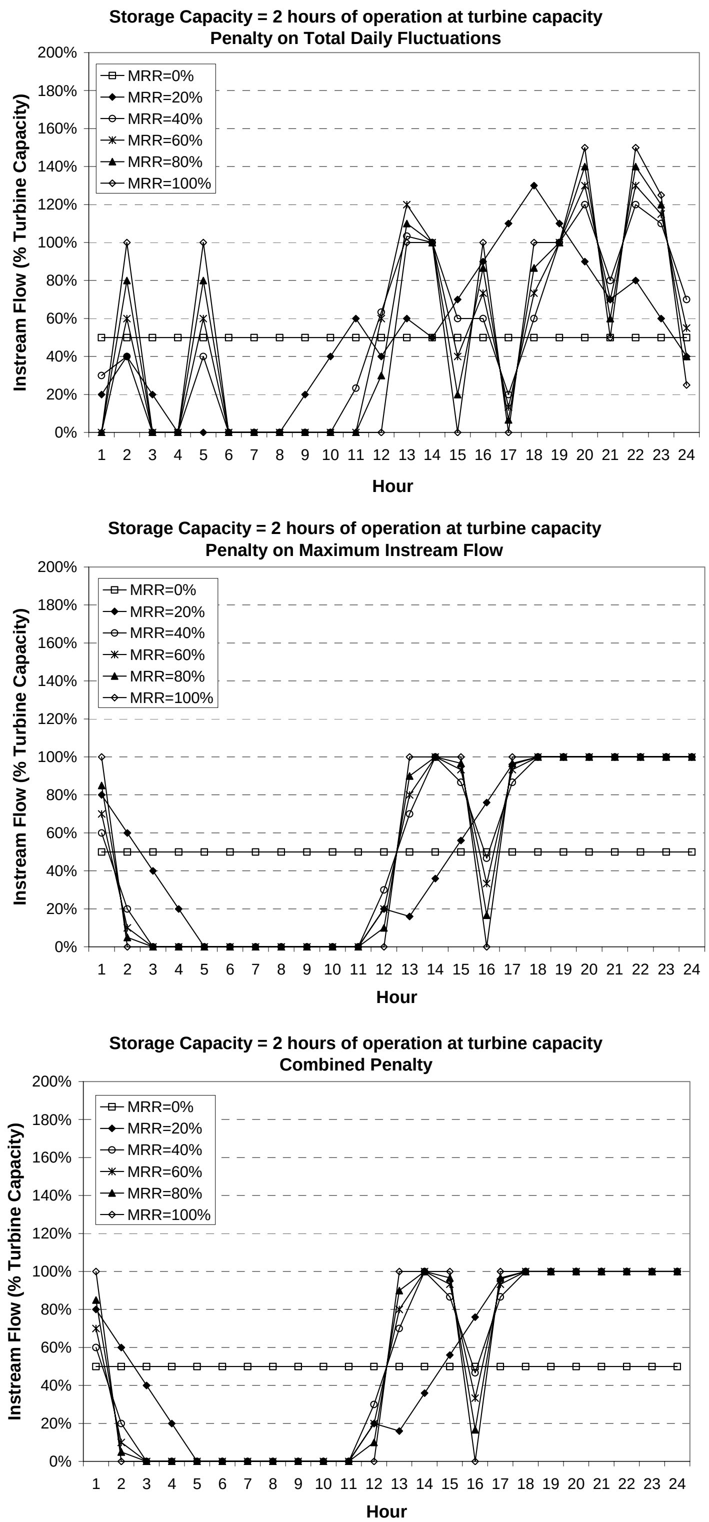


Figure 3.16: Alternative instream flow patterns with larger afterbay under MRR

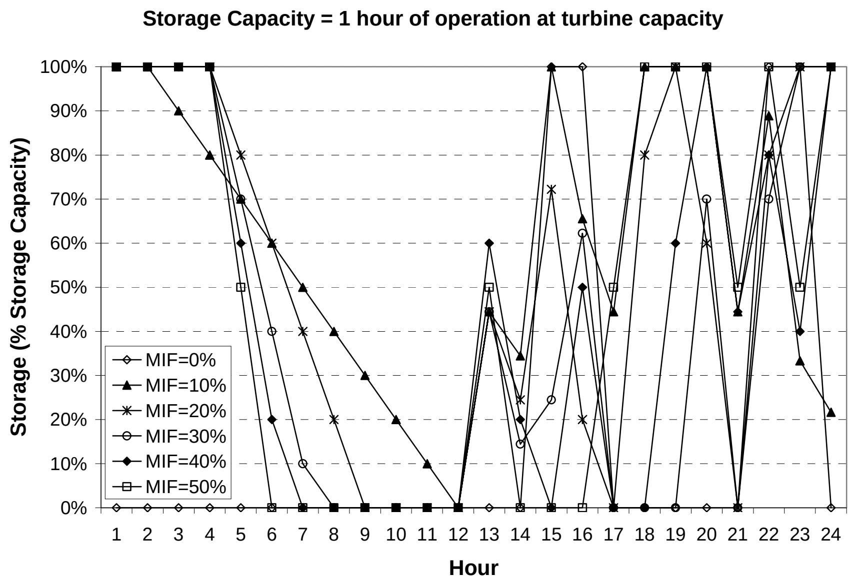
3.5.4 Re-regulation reservoir storage

This section shows the storage cycle in the re-regulation reservoir for a daily water availability of 50% the maximum usable. Fig. 3.17 shows the results for the case with MIF and no constraint on ramping. In general, for an afterbay size equivalent to one hour of operation at turbine capacity, the afterbay is full by midnight and empties during the morning, then it shows a couple of drawdown cycles during the on-peak period. The afterbay empties faster in the morning as the MIF requirement increases. For MIF=10% the afterbay starts empting at 1 AM and finishes by 11 AM. In contrast, when the minimum flow requirement is most stringent (50%), the afterbay takes only an hour to empty. Immediately after noon, the storage increases to about 50% of its capacity and then the behavior differs depending on the MIF level. For MIF=10% the afterbay never empties during peak hours, the lowest observed storage is about 30% capacity. When a minimum release equal to 50% of turbine capacity is enforced, the afterbay is empty between 1 PM and 3 PM, and then it fills to reach storage capacity by 5 PM. From there storage fluctuates between full and 50% until midnight. In the unconstrained case (MIF=0%), the reservoir is full during two short periods right after the hours when energy is most expensive, and remains empty the rest of the day. Interestingly, when no minimum release is required, the afterbay is irrelevant for hydropower revenues and therefore an alternative storage pattern would be to bypass it and keep it empty the entire day. This is consistent with the several alternative instream flow patterns shown in the previous section. Patterns in the releases to the stream are directly related to operational patterns for the afterbay.

For an afterbay twice as large, the morning drawdown takes longer than with a smaller storage capacity, for all MIF levels. However, the afterbay is never full for MIFs below 20% the turbine capacity. Moreover, during peak hours the afterbay only reaches capacity for the most stringent release requirement, under which its behavior is similar to that observed for the smaller afterbay.

The effect of maximum ramping rates on the storage sequence with no minimum release requirement is presented in Fig. 3.18. The smaller re-regulation reservoir tends to fill at least twice during the on-peak period, but it only reaches full capacity when the smallest or the largest ramping rates are allowed. Except when no ramping is allowed and consistent with the results in the preceding section, maximum storages tend to decrease as the ramping constraint becomes more stringent. This seems counterintuitive, since use of re-regulation capacity is expected to decrease as more flexible operations are allowed. For most MRR levels, highest storage levels are observed between 2 PM and 3 PM, and between 9 PM and 10 PM. An afterbay with capacity to store a volume equivalent to two hours of hydropower releases at turbine capacity, only reaches full capacity when no ramping or 10% of turbine capacity is allowed. In all other cases, the afterbay reaches at most 50% of its capacity during the on-peak hours, with highest storages between 5 PM and 6 PM, and between 9 PM and 10 PM. It seems that, under ramping rate constraints alone, a rather small afterbay is needed unless very little ramping is allowed. This is consistent with the revenue results (Fig. 3.5), where the effect of the afterbay only differs between both capacities for allowed ramping rates smaller than 10% the turbine capacity.

Fig. 3.19 shows the storage cycles under various MIFs and ramping rates restricted to 10% turbine capacity per hour. Unlike the previous cases, a clear pattern is followed for all MRR levels. The pattern is similar for both storage capacities. As in the case with MIF alone, a drawdown occurs during the off-peak hours and the reservoir fills up during on-peak hours. The afterbay reaches full capacity for all MIF levels.



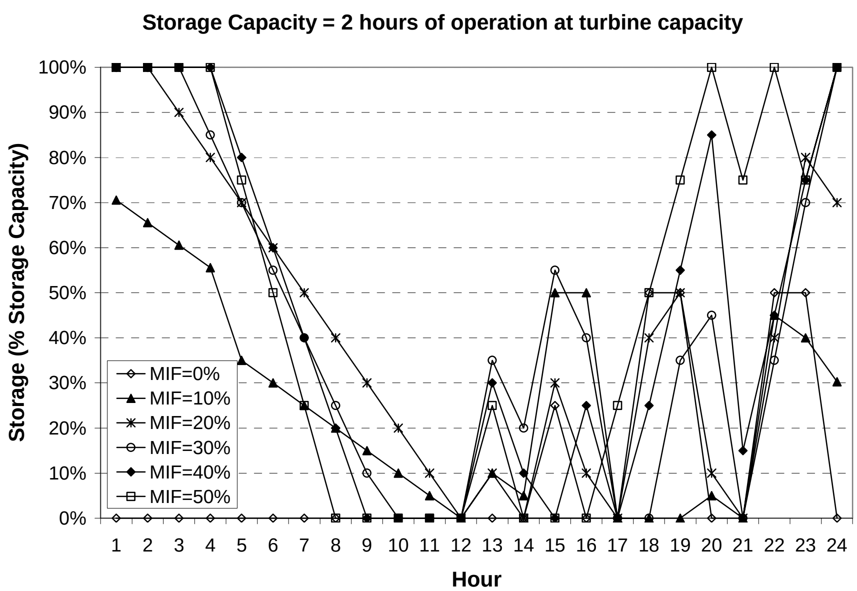
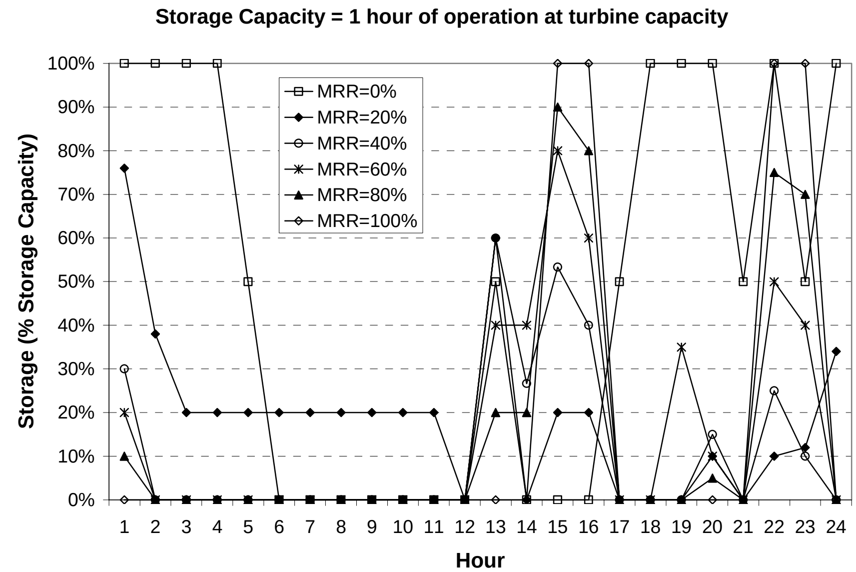


Figure 3.17: Re-regulation reservoir storage under MIF



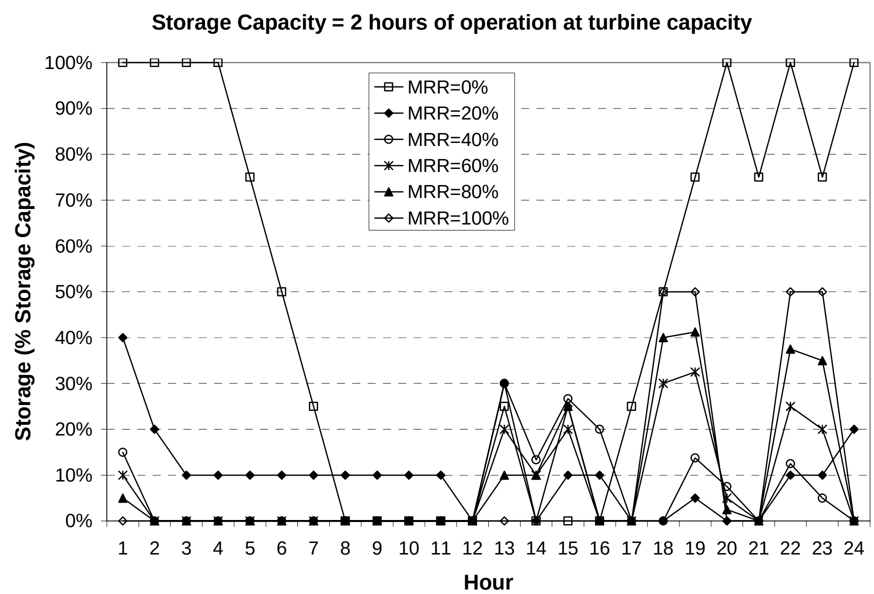


Figure 3.18: Re-regulation reservoir storage under ramping constraints

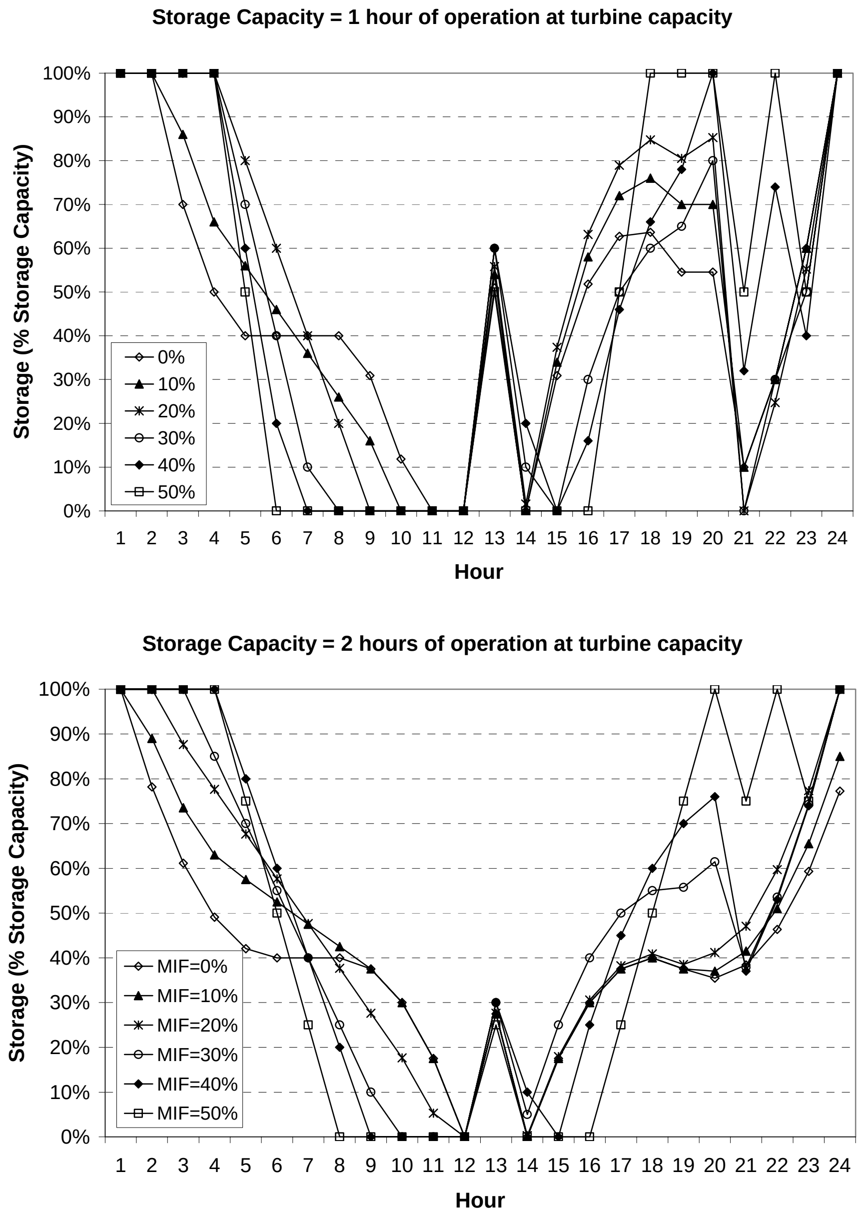


Figure 3.19: Re-regulation reservoir storage under MIF and 10% maximum ramping rate

Afterbay storage cycles for the alternative instream flow patterns presented in the previous sections are shown in Figs. 3.20 through 3.23. For the case of MIF alone with smaller afterbay (Fig.3.20), a much more regular pattern is followed for all MIF levels during the peak hours. Observed storages are highest after hours of high prices. Similar patterns are observed in Fig. 3.21, for a larger afterbay under MIF constraints.

Under ramping constraints alone, no clearer patterns than those observed for the original results are identified, although more storage tends to be used when total fluctuations are penalized as compared to the original results for the larger afterbay (top graph on Fig.3.23).

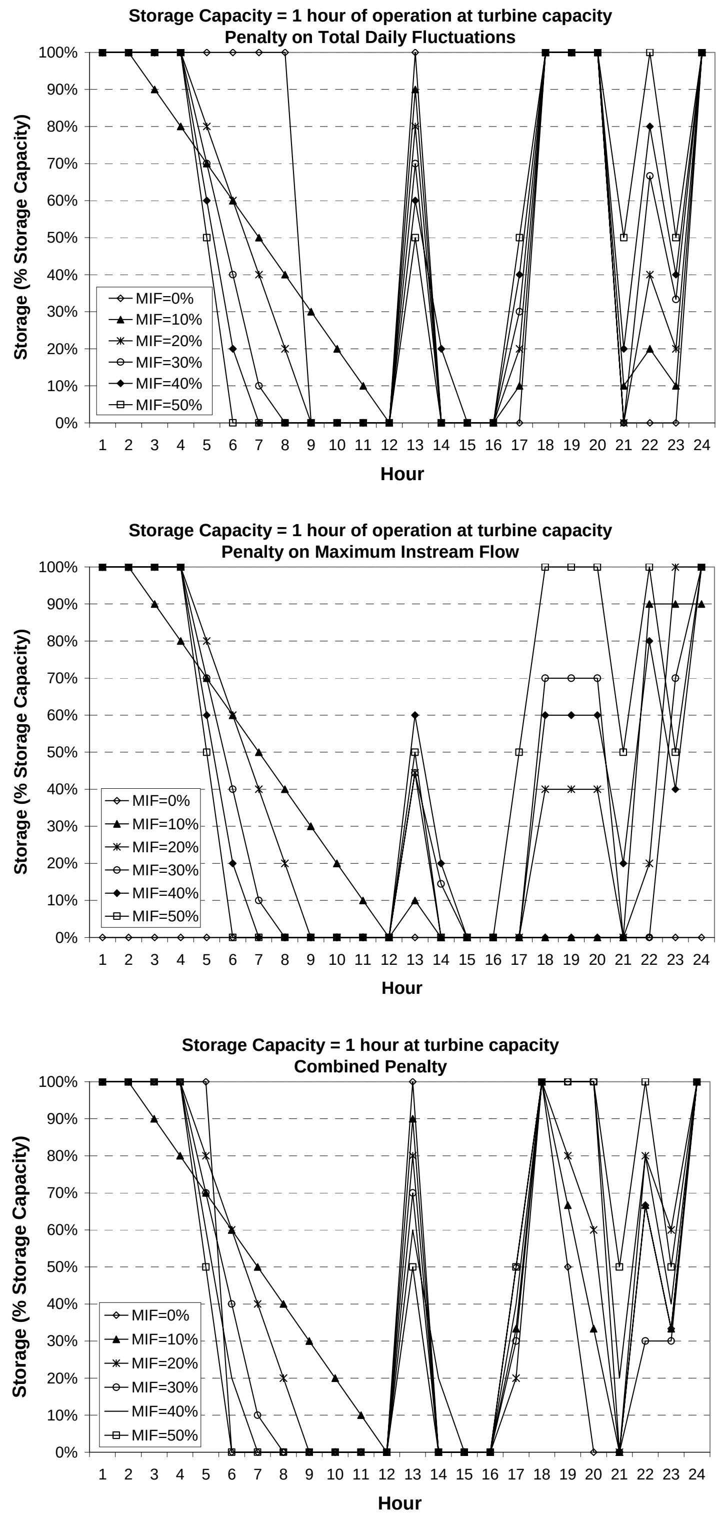
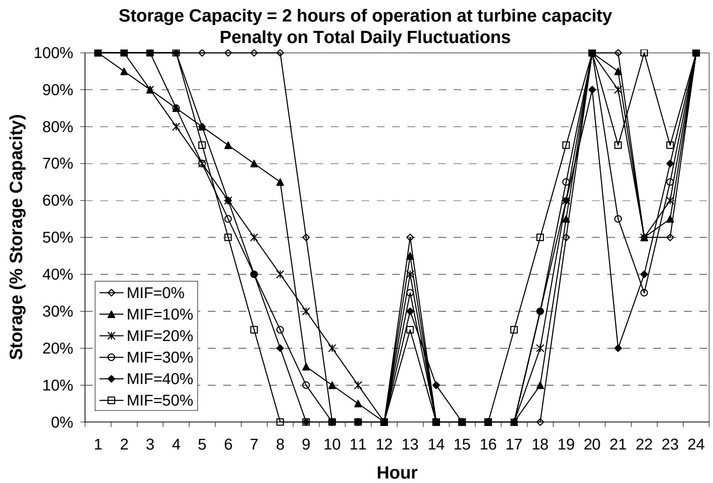
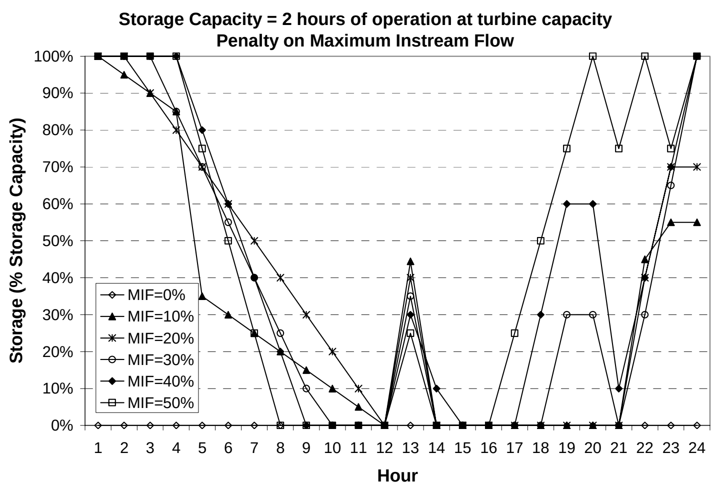


Figure 3.20: Alternative storage patterns for smaller afterbay under MIF





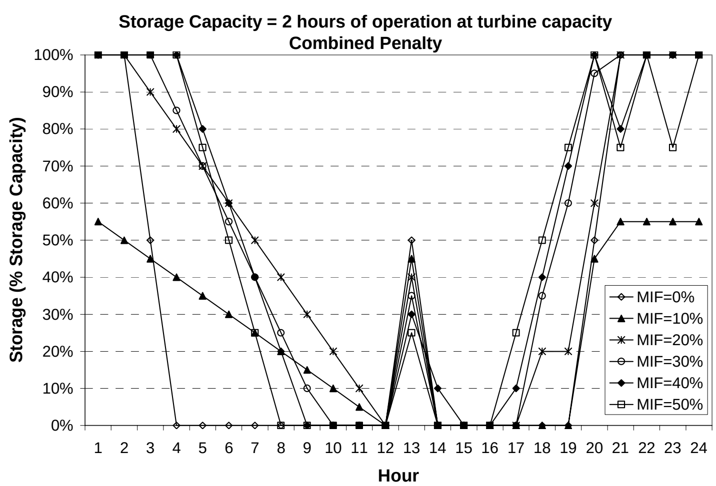


Figure 3.21: Alternatives storage patterns for larger afterbay under MIF

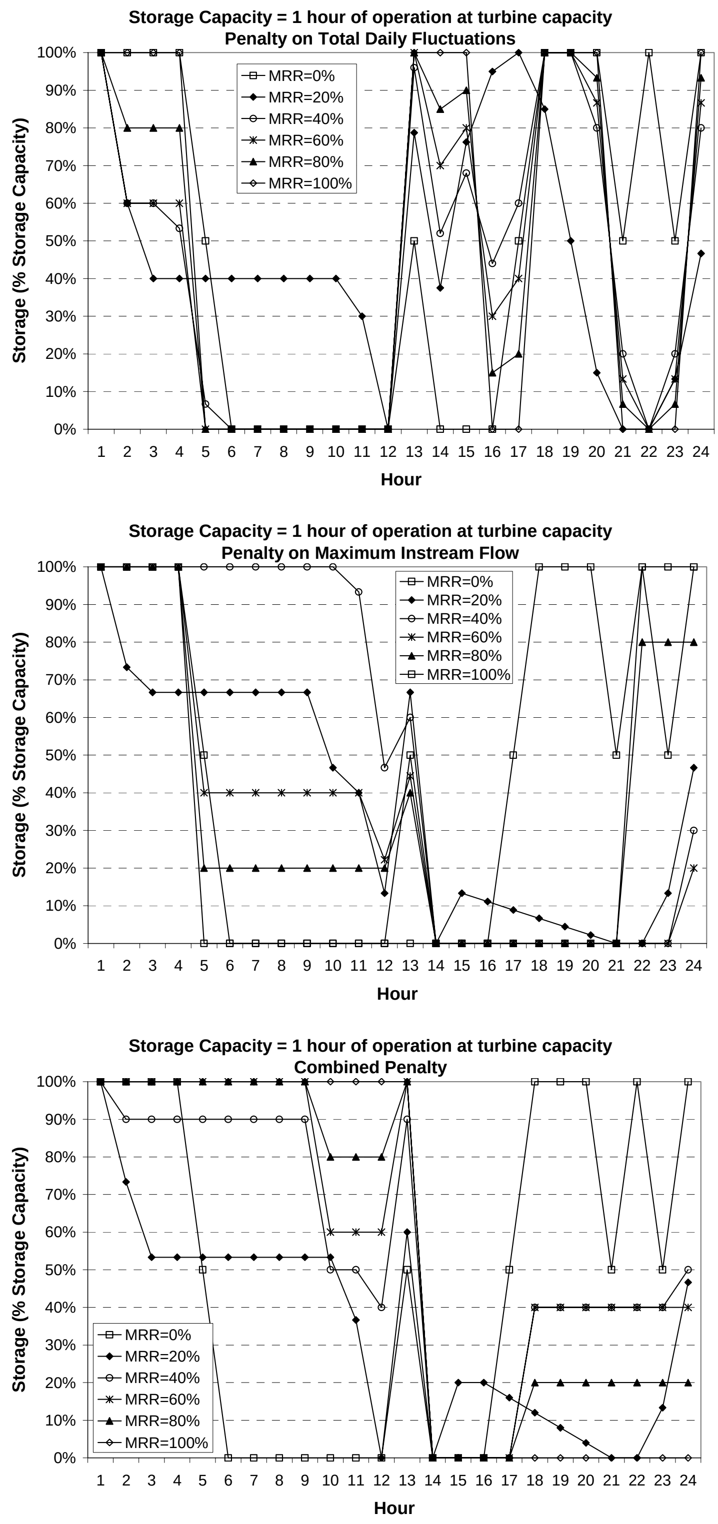


Figure 3.22: Alternative storage patterns for smaller afterbay under MRR

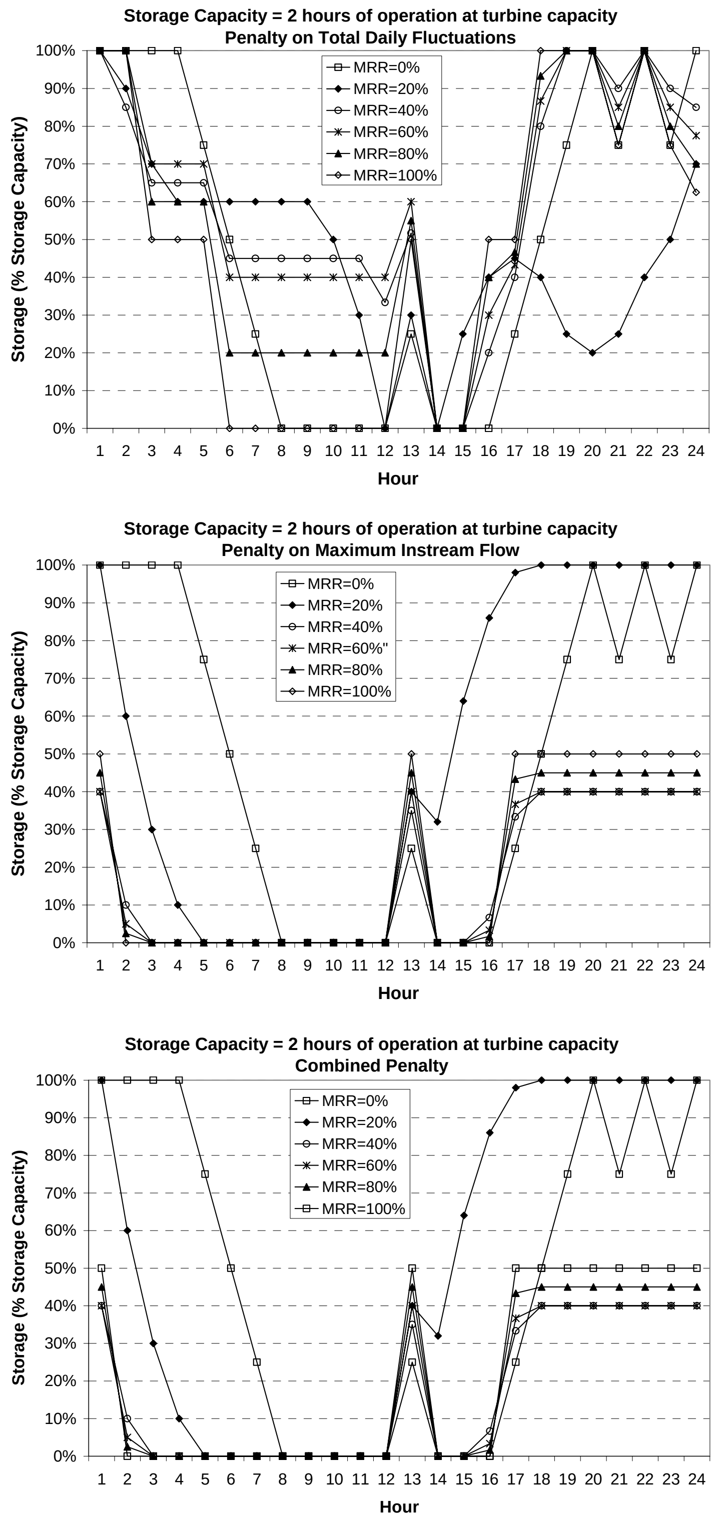


Figure 3.23: Alternative storage patterns for larger afterbay under MRR

3.5.5 Marginal value of turbine capacity (MVTC)

The value of a unit increase in turbine capacity is an important economic indicator of the system. It helps guide decisions on capacity expansion. Fig. 2.24 shows the effect of MIF requirements on the marginal value of turbine capacity, for selected levels of total daily water availability. No ramping constraint is imposed in this case. As expected, the MVTC decreases as the required release to the stream increases, because less water can be optimally allocated to hydropower generation. The value increases as does the daily hydropower release target, because more water is available and then additional generation capacity is more valuable. Without an afterbay, the MVTC reduces to zero when the required release to the stream approaches the average water availability. At that point, even if turbine capacity was increased, the minimum flows make it impossible to allocate more water for generation during the most valuable hours. With an afterbay, the decrease in MVTC due to MIF requirements is less pronounced. The afterbay dampens or eliminates the connection between hydropower release and streamflow. This effect is slightly stronger for an afterbay twice as large.

The effects of restricted ramping rates with no required minimum flow are shown in Fig. 3.25, where each series represent a level of daily hydropower release target. For all target release levels and afterbay sizes, the MVTC increases as higher ramping rates are allowed, i.e., as ramping becomes less constrained and more flexible operations are possible. With an afterbay, the MVTC reaches its unconstrained level after ramping rates of about 18% and 10% of turbine capacity. This is consistent with the range of ramping rates where the optimal daily hydropower revenue was affected.

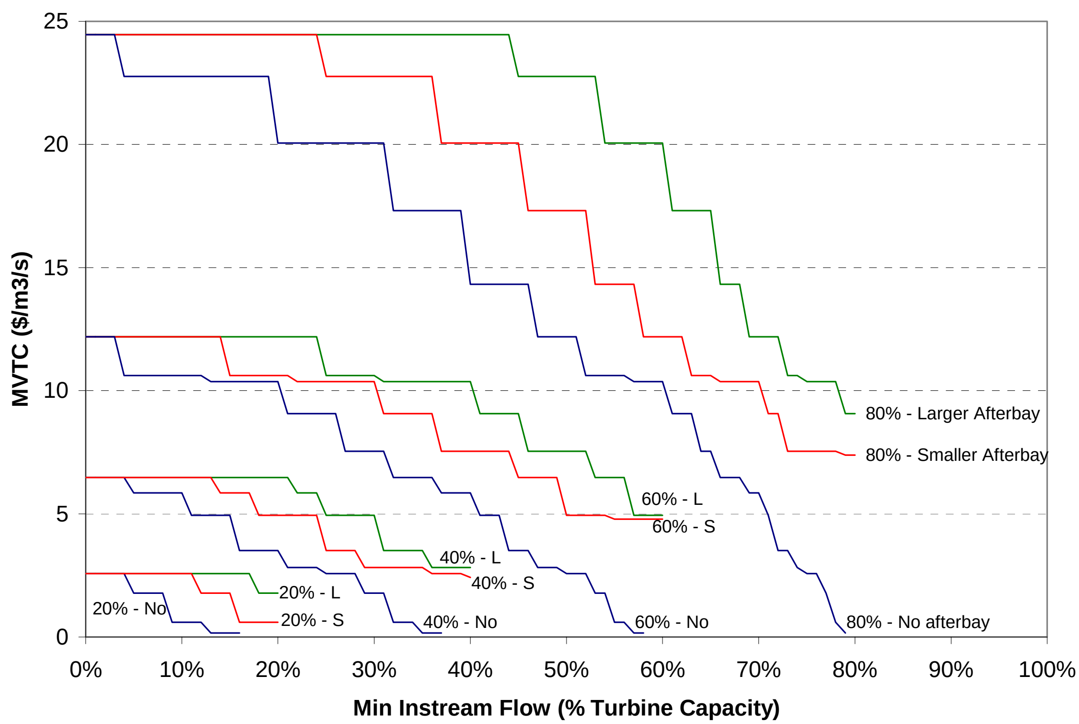


Figure 3.24: Effect of MIF on the marginal value of turbine capacity

Finally, the MVTC as a function of MIF requirement for a maximum ramping rate of 10% is shown in Fig.18. Clearly the MVTC's in this case are lower than those with

MIF requirement alone. Without an afterbay, the MVTC is zero for daily water availability at or under 40% of the maximum, for all feasible levels of required releases to the stream. Comparing the results for the two afterbay sizes, the larger afterbay has larger MVTC's, especially when required releases to the stream are large.

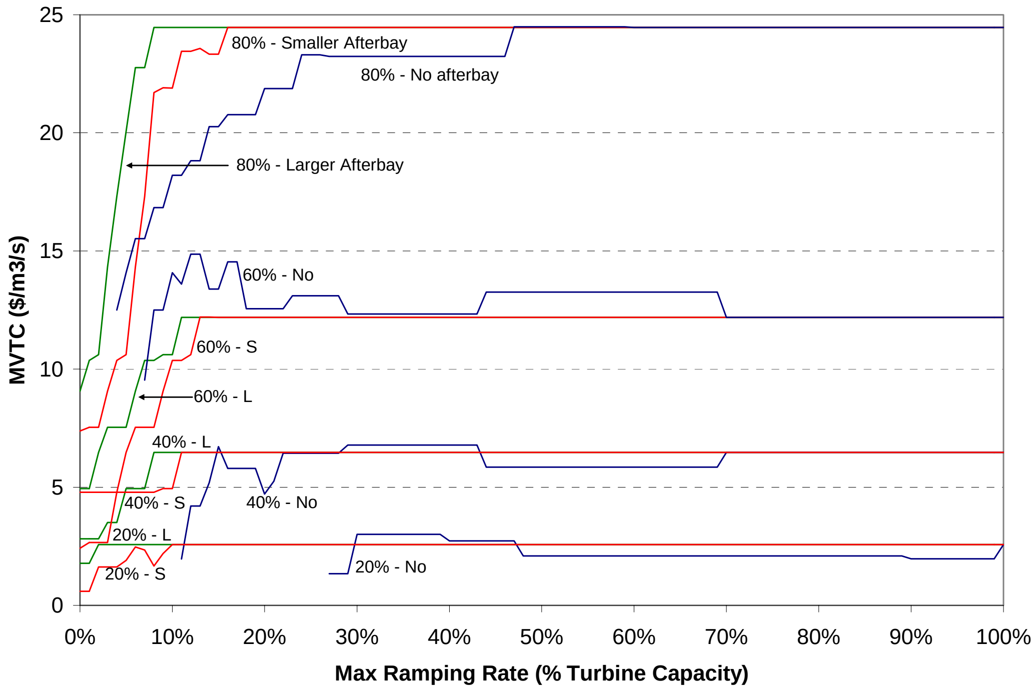


Figure 3.25: Effect of ramping constraint on the marginal value of turbine capacity

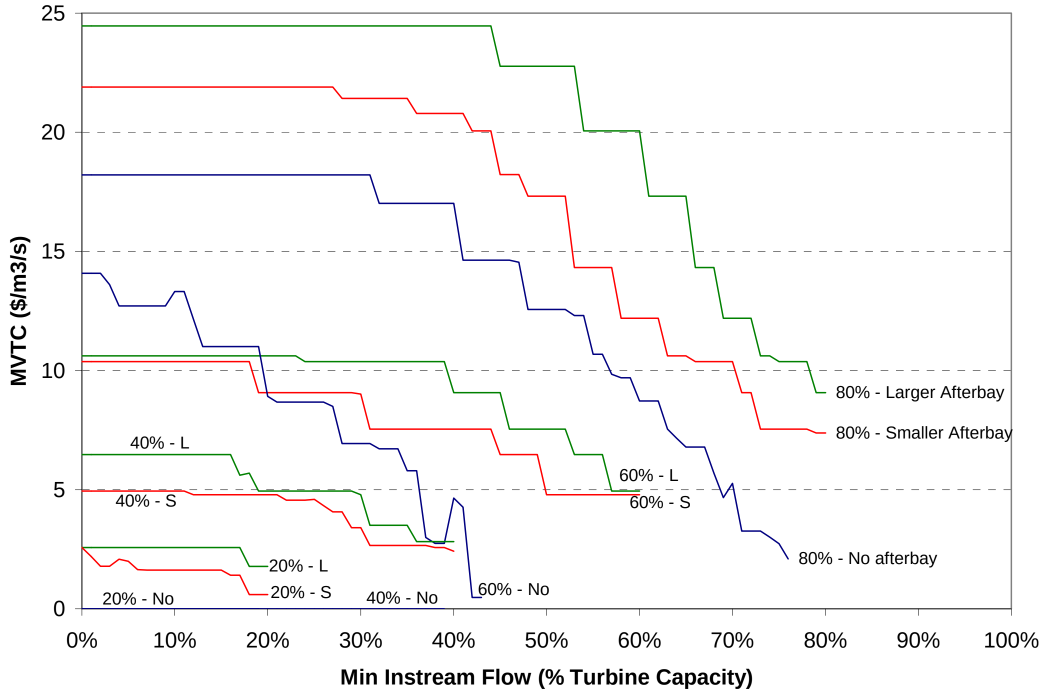


Figure 3.26: Combined effect of MIF and maximum ramping constraint on the marginal value of turbine capacity

3.6 Conclusions

This chapter presented the results of an optimization model that simulates the operation of a reservoir-afterbay hydropower complex, under regulatory constraints defining minimum releases to the stream and the maximum rates of release change between two consecutive hours. The linear programming formulation solves the problem for periodic operations without specifying timing on the drawdown-refill cycle.

Tradeoffs between economic benefits and instream flow requirements were explored. Constraints on releases to the stream have an economic impact on hydropower revenues. However, a re-regulation reservoir can mitigate this effect by dampening the connection between hydropower generation flows and releases to the stream. Stringent MIF requirements alone can reduce revenues by 15% when no re-regulation capacity is in place. If a re-regulation reservoir is introduced, the revenue reduction is 9% and 6% for afterbay capacities equivalent to one and two hours of operation at turbine capacity, respectively. Similar effects where observed for restricted ramping rates alone. However, it was observed that, for the cases with afterbay, only very stringent ramping rates, below 15% of turbine capacity, affect hydropower revenues. Differences in revenues between both afterbay sizes are only observed for allowed ramping rates below 10% of turbine capacity. Both afterbays perform equally well in terms of revenues for less stringent ramping constraints. When higher hourly fluctuations of instream flows are allowed, revenues reach the unconstrained levels. The effect of combined minimum flow and ramping constraints was studied for a maximum ramping rate of 10% turbine capacity and varying levels of minimum required releases to the stream. The results are very similar to those obtained for MIF alone. Therefore, limiting ramping rates to 10% of the turbine capacity per hour has no additional effect on revenues to that attributed to minimum required releases to the stream.

The magnitude and timing of hydropower generation flow decision were also studied. In general, hydropower releases tend to follow the price pattern characterized by high prices during the PM hours and lower prices during the rest of the day. These two periods can be considered on-peak and off-peak, respectively. Constraints on releases to the stream restrict the ability of the system to follow the daily pattern of energy prices. Minimum required releases to the stream force the system to generate electricity during less valuable hours, when no afterbay is available. With an afterbay, operations are not affected for MIFs up to 10% and 20% of turbine capacity, for the smaller and larger storage capacity, respectively. Constraints on ramping rates cause more uniform hourly releases. As larger ramping magnitude is allowed, more generation is observed during on-peak hours. When re-regulation is possible, only very severe constraints on ramping (less than 20% of turbine capacity) have an impact on hydropower release decisions.

Releases to the stream match the minimum required during off-peak hours, and are higher and more fluctuating during on-peak hours, even doubling turbine capacity when re-regulation is available. The afterbay tends to empty during the off-peak period and it fills up, often more than once, during on-peak hours. Several alternative instream flow patterns were explored by introducing penalties on the sum of daily fluctuations and/or the maximum hourly release during the day. All alternative solutions gave the same optimal revenue, revealing the existence of several alternative operational patterns for the afterbay.

Afterbay storage results show a drawdown during the morning off-peak hours and some refill cycles during peak hours. Storages are highest after hours of high energy price (and therefore high hydropower generation).

Finally, modeling has proven a useful tool to study a reservoir-afterbay complex under parametrically varying instream flow constraints and daily hydropower release targets.

3.7 References

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CHAPTER 4

REPRESENTATION OF ENERGY PRICES IN LONG- AND MEDIUM-TERM OPTIMIZATION OF HYDROPOWER RESERVOIR OPERATIONS

4.1 Introduction

Optimization models are commonly used for hydropower reservoir operations at different time scales, ranging from seasonal operation planning to daily, hourly, and real-time operations. Before energy market liberalization, the problem was formulated as cost minimization by a central utility planner (Jacobs and Schultz, 2002). With energy markets in place and decentralization of electricity generation authority, revenue maximization has become the driver for operations. Since price is a market output, this process involves an increase in the uncertainty facing power operators.

In short-term models, with an hourly time step and time horizon of a few days, using an average price during each time step should work well, because it matches the time frame of market clearing prices developed by the Independent System Operator (ISO). However, at longer time scales, assuming a single representative price for each time step (week, month, etc) can be misleading, especially if the average or median of the full historical record for the period in question is considered. Using an average price most likely underestimates revenues, because the actual average price does not necessarily include all the hourly prices during the period in question, but only those corresponding hydropower generation times. Including prices at every hour does not recognize the nature of peaking operations. Generally, reservoir releases will be allocated for generation during hours with higher energy prices. Unfortunately, using average energy prices has been the common in the water resources literature. Efforts to improve this simplification have used peak and off-peak prices, with an upper bound on the number of hours of generation at peak energy price (e.g. Grygier and Stedinger, 1985; Trezos and Yeh, 1987). California's PGE scheduling system SOCRATES (Jacobs *et al*. 1995) divides each weekly or monthly period into 4 sub-periods, which distinguishes between peak and off-peak generation during weekdays and weekends.

Instead of a complete representation of energy prices, research has focused on development of efficient algorithms for multi-reservoir systems (e.g. Turgeon and Charbonneau, 1998; Pereira and Pinto, 1985), and incorporation of hydrologic uncertainty (Kelman *et al*., 1990; Tejada-Guibert *et al*., 1995). Little consideration has been given to uncertainty in the energy prices, which drive operational decisions in decentralized systems. Within the energy systems literature, work has been directed to developing statistical price forecasting models (Nogales *et al.*, 2002) and explicit economic models of electricity markets, including optimal bidding strategies for generators under perfect competition (Pritchard *et al*. 2005) and duopolistic models (Scott and Read, 1996).

This chapter develops a method to incorporate hourly price and operational information into revenue functions at coarser daily, weekly, or monthly modeling time scales. The proposed method approximates the results that would be obtained by an embedded hourly optimization procedure, simplifying the computational implementation of optimization models for operations at the coarser time scales. The method assumes the reservoir operator has a perfect foresight of a duration or frequency curve of hourly prices for the relevant time scale. This extends and develops the work of Madani and Lund (2008), who considered hydropower systems with constant head, to storage-dependent head and releases constrained by minimum instream flows.

4.2 Price duration curve and optimal operating rules

A common objective for hydropower operations is to maximize the total revenue obtained from generation during a time horizon T, typically discretized into smaller decision periods ΔT. Time horizons of one year with weekly or monthly decision are a common choice.

In general, the total revenue due to energy sales during a period ΔT is given by:

$$B = \int_{t_0}^{t_0+\Delta T} P(t) \cdot W(t) \cdot dt \tag{4.1}$$

Where $P(t)$ is the energy price at time t and $W(t)$ is the power generation during time t given by:

$$W(t) = \varepsilon \cdot \gamma \cdot Q(t) \cdot h(t)\,, \tag{4.2}$$

Where ε is the generation efficiency and γ is the specific weight of water. $Q(t)$ and $h(t)$ are the release rate and head at time t, respectively.

Embedding (4.2) into (4.1) we have:

$$B\big(P(t), Q(t), h(t)\big) = \int_{t_0}^{t_0+\Delta T} P(t) \cdot \varepsilon \cdot \gamma \cdot Q(t) \cdot h(t) \cdot dt \tag{4.3}$$

Discretizing ΔT into N sub-periods Δt (e.g. one hour), (4.3) becomes:

$$B\big(P_i, Q_i, h_i\big) = \sum_{i=1}^{N} P_i \cdot \varepsilon \cdot \gamma \cdot Q_i \cdot h_i \cdot \Delta t$$

A precise representation of the intra-period problem would involve the maximization of B subject to operational constraints on release flows at each hour. The problem also would be subject to an initial storage and total water availability for the operational period ΔT.

Without constraints other than turbine flow capacity and total water release allocation during ΔT, the optimal operational rule is straightforward. Releases are allocated to hours during the operational period in the order of decreasing price until water allocation is exhausted. Given a total volume V of water available for generation and turbine flow capacity C (Volume/hour), the total number of hours of operation at full capacity is $N_V = V / C$. Then the percentage of hours of operation is:

$$f_V(\%) = \frac{N_V}{\Delta T} \cdot 100$$

The duration curve for hourly energy prices during a given period ΔT relates a given price level P with the fraction of ΔT during which prices have equaled or exceeded P. The key concept of the method is to relate this fraction to the percentage of the total energy that could be generated if the plant was generating at capacity during the entire operational period. This allows the actual average price to depend on the level of total generation or proportion of hours generated. The operator cannot influence the market price. Hourly prices are exogenous to the optimization, but perfect foresight of the duration curve by the operator is assumed. Therefore, for peaking generation, the average price realized depends on the portion of the price duration curve covered by the operations, beginning with the highest-priced hours.

Given an energy price duration curve $P(f)$, the optimal operating rule is to generate at turbine capacity during all hours when the price $P \geq P(f_V)$. This is illustrated in Fig. 4.1, which also shows a typical peak/off-peak price structure approximation. Since operational decisions are made at the beginning of every hour, our approach assumes the operator has a perfect 1 hour-lead price forecast, which is almost the case in the field, as well as a perfect knowledge of the price duration curve.

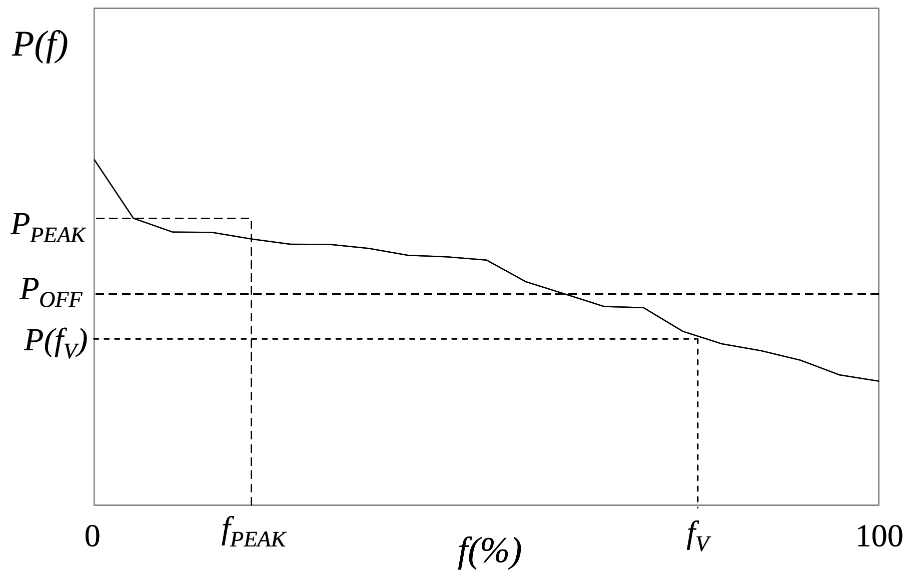

Figure 4.27: Price duration curve and 2-block price approximation

With the operational scheme just described, the total revenue during the period ΔT can be obtained as a function of the turbine capacity, the total volume allocated V and the head at each period:

$$B(C, f_V, h_i) = \sum_{i \in I(f_V)} P_i \cdot \varepsilon \cdot \gamma \cdot C \cdot h_i \cdot \Delta t \tag{4.4}$$

Where $I(f_V)$ is the set of hours when the price is higher than $P(f_V)$, obtained from the price duration curve. Fig. 4.2 shows the set $I(f_V)$ within a weekly time series for selected f_V values.

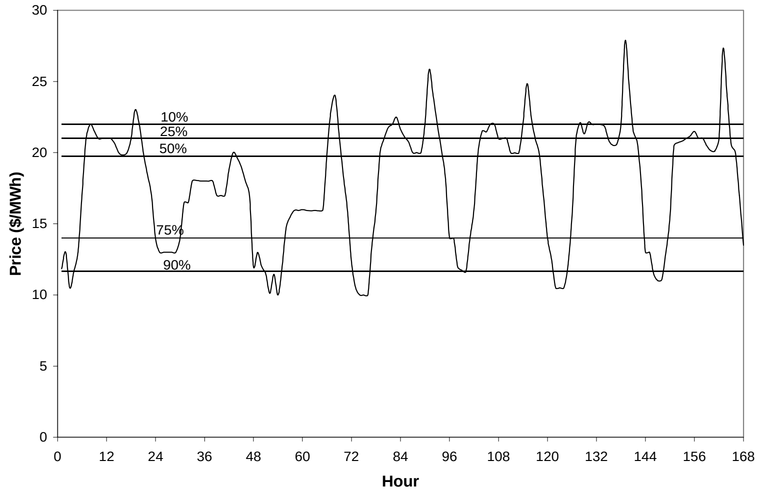

Figure 4.28: Example price time series including selected percentiles

4.3 Approximation of optimal revenues

From this perspective and assumptions, an optimal revenue function can be estimated for various conditions.

4.3.1 Constant head

When changes in storage do not significantly change total head, one can assume a constant head. This occurs when V is small relative to total storage or when most head is produced by a very long penstock where large changes in reservoir stage do not greatly affect total head. Using this approximation, (4.4) becomes:

$$B(C, f_V, h) = \varepsilon \cdot \gamma \cdot C \cdot h \cdot \Delta t \sum_{i \in I(V)} P_i = \varepsilon \cdot \gamma \cdot C \cdot h \cdot \Delta t \cdot N_V \cdot \overline{P}(f_V) = E_V \cdot \overline{P}(f_V) \qquad (4.5)$$

where E_V is the total energy that can be generated with a volume V of water at constant head and $\overline{P}(f_V)$ is the average of all prices greater than $P(f_V)$. With constant head, the revenue depends only on the total volume of water available but not on the reservoir storage level.

Given a representative decreasing sorted sample of prices for the duration curve, the function $\overline{P}(f_V)$ can be calculated as the moving average of prices up to $P(f_V)$. Fig. 4.3 shows the moving average curve corresponding to the duration curve shown in Fig. 4.1.

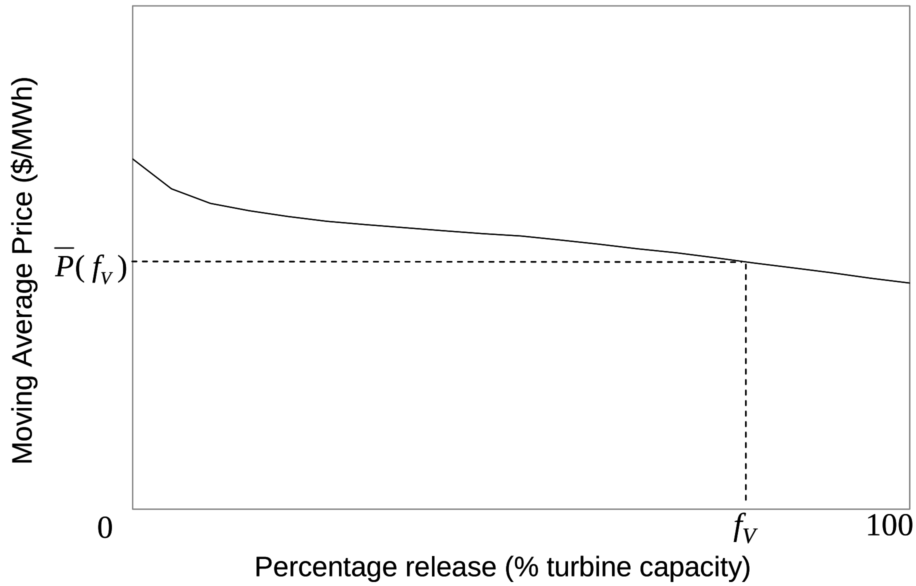

Figure 4.29: Moving average curve as a function of percentage of hours of generation

Given the turbine flow capacity C and the constant head h, the revenue curve as a function of the percentage volume allocation f_V can then be obtained from (4.5). Fig. 4.5 shows the revenue curve corresponding to the price curve in Fig. 4.4 for hypothetical values of the turbine capacity and head. It shows decreasing marginal revenues.

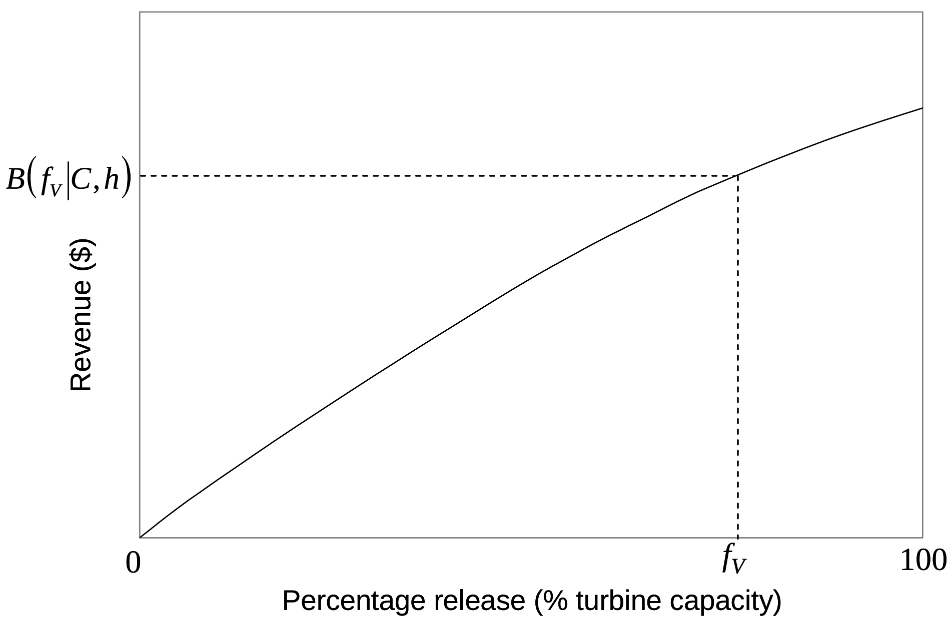

Figure 4.30: Revenue curve given turbine capacity and head

4.3.2 Storage-dependent head

When total head depends markedly on reservoir storage level, the estimation of total revenue becomes more complicated, because one hour of operation will result in different energy generation depending on the reservoir level during each hour. In other words, the step from (4.4) to (4.5) cannot be done. However, the operational rule remains valid, only the estimation of total revenue becomes more complicated as it depends on the price-storage pairs that are realized during operations. Fortunately, upper and lower bounds for revenues can be calculated assuming the best and worst case scenarios for price-storage pairs, respectively. In the best case scenario, high prices perfectly match high storage (head) levels. The contrary is assumed in the worst case scenario, with most releases occurring in the lower storage (head) times. Estimation of these bounds only requires that we know the increase or decrease in reservoir volume of the operational period, and that the net rate of change in storage be approximately steady of the operational period. For these cases, Eq.4.4 becomes:

$$B = \varepsilon \cdot \gamma \cdot C \cdot \Delta t \cdot \sum_{i \in I(V)} P_i \cdot h_i \qquad (4.6)$$

In reality, the revenue will be somewhere between those two bounds. The result will depend on the price sequence effectively seen by the operator and on how the storage evolves through time. The latter will depend on the balance between releases and inflows to the reservoir. However, as shown in Fig.4.4, the sequence of price values during generation hours tend to be periodic, for any frequency level. These sequences are obtained from the truncated total time series obtained for each generation frequency level as shown in Fig.4.2. In this particular series, lower peak prices are observed at the beginning of the sequence. This is explained because the week started on a weekend, which is an off-peak period. Other than that, no marked bias on price levels seems to exist during weekdays.

The hourly storage sequence is determined by water balance:

$$S_{i+1} = S_i + \left(I_i - Q_i\right) \cdot \Delta t - e_t \qquad (4.7)$$

Where I_t and e_t are the inflow to and evaporation from the reservoir during the i^th hour of the week, respectively. Assuming the operational scheme previously described we have:

During hours of generation (4.7) becomes: $S_{i+1} = S_i + \left(I_i - C\right) \cdot \Delta t - e_t$

During hours without generation (4.7) becomes: $S_{i+1} = S_i + I_i \cdot \Delta t - e_t$

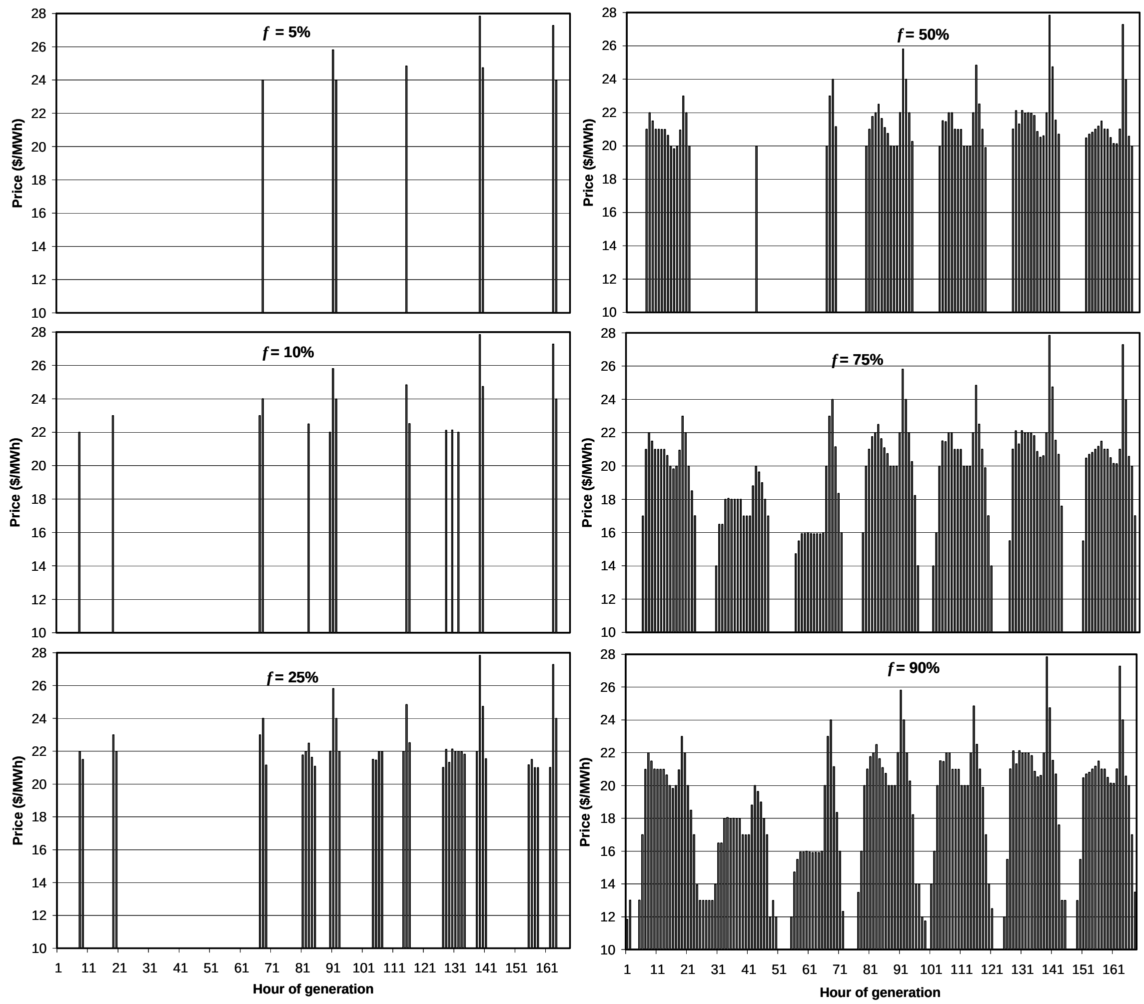

Figure 4.31: Example price sequence during hours of operation for different frequency levels (No release takes place in hours between price bars)

Thus, reservoir storage will increase or decrease depending on the hydrologic and atmospheric conditions during the operational period. In California's Sierra Nevada mountains, spring has large inflows due to snowmelt and moderate evaporation, so reservoirs tend to refill overall. During summer, evaporation increases and inflows decrease, so refill during non-generation hours cannot be guaranteed. In other words, the net inflow, along with the release decision at every period, determines the change in storage.

Since the objective of this chapter is to develop simple estimates of the total revenues during weeks or months, a detailed analysis of hourly inflow and evaporation series is beyond our scope. A simple estimate can be obtained using (4.5) with the average between the initial and final head during the period, which requires only the initial and final storage for each period ΔT . The final storage can be calculated from the initial storage and net inflow during the entire period.

4.3.3 Environmental Constraints on Releases

Often, environmental constraints take the form of minimum instream flows (MIFs) and maximum ramping rates (MRRs). When these restrictions are imposed, the optimal operational strategy departs from the simple one described above. In the case with MIF alone, the approach can be slightly modified in that the total volume V cannot be freely allocated by the operator. However, the described procedure remains valid if the "effective" volume available for discretionary release is considered, i.e. the volume that can be allocated by the operator during hours of high price. This volume includes the minimum release in those hours.

Given a total volume V available for the entire period and a minimum flow $Q_{\min}$, the percentage of the time f_{EFF} that operation at full capacity can take place is given by:

$$V = V_{EFF} + V_{MIN} = C \cdot T \cdot f_{EFF} + Q_{\min} \cdot T \cdot (1 - f_{EFF}) \tag{4.8}$$

Solving for f_{EFF}, with $Q_{\min} = \alpha \cdot C$ we obtain: $f_{EFF} = \dfrac{(f_V - \alpha)}{(1-\alpha)}$ (4.9)

Similar to (4.4), the total revenue is given by:

$$B(C, f_V, h, \alpha) = \varepsilon \cdot \gamma \cdot h \cdot \Delta t \cdot \left\{ C \cdot \sum_{i \in I(V_{eff})} P_i + \alpha \cdot C \cdot \sum_{i \notin I(V_{eff})} P_i \right\} \tag{4.10}$$

Eq. (4.10) simply separates the revenues between those hours when discretionary release over the MIF is allocated and those when only the MIF is released.

Defining the excess turbine capacity over the MIF as $Q_{ex} = C \cdot (1-\alpha)$, after some algebra (4.8) becomes:

$$B(C, f_V, h, \alpha) = \varepsilon \cdot \gamma \cdot h \cdot \Delta t \cdot \left\{ C \cdot (1-\alpha) \cdot \sum_{i \in I(V_{eff})} P_i + \alpha \cdot C \cdot \sum_{i=1}^{N} P_i \right\}$$

In terms of the average prices:

$$B(C, f_V, h, \alpha) = \varepsilon \cdot \gamma \cdot h \cdot \Delta t \cdot \left(C \cdot (1-\alpha) \cdot N \cdot f_{EFF} \cdot \overline{P}_{EFF} + \alpha \cdot C \cdot N \cdot \overline{P} \right) \tag{4.11}$$

Where $\overline{P}_{EFF} = \overline{P}(f_{EFF})$ and $\overline{P}$ is the average price for the entire period of interest.

Substituting (4.9) in (4.11) we obtain:

$$B(C, f_V, h, \alpha) = \varepsilon \cdot \gamma \cdot h \cdot C \cdot \Delta t \cdot N \cdot \left(\overline{P}_{EFF} \cdot (f_V - \alpha) + \overline{P} \cdot \alpha \right) \tag{4.12}$$

Rearranging and expressing in terms of energy and prices we obtain:

$$B(C, f_V, h,) = \left(E_V - E_{MIN} \right) \cdot \overline{P}_{EFF} + E_{MIN} \cdot \overline{P} \tag{4.13}$$

Where E_{MIN} : energy generated with minimum release

E_V : total energy generation

The effect of a minimum release on revenues is clear if we compare Eq.(4.13) with the expression in Eq.(4.5). With minimum flows, since the MIF must be released at all times, the value of energy associated with the MIF is equal to the average price over the period.

The energy in excess of the minimum energy is sold at a higher price, determined by the allocation of excess water to each hour in order of decreasing energy price.

With MRRs the optimal strategy is not very straightforward. However, as shown in the previous chapter, the effect of MRRs on revenues can be easily determined for any system based on a normalized approach. This provides the percentage reduction of revenue relative to the unrestricted optimum, for given MIFs and MRRs expressed as a percentage of turbine flow capacity. This exercise will not be done in this chapter and is a possible extension of the method presented here.

4.4 Numerical Example

A numerical example is used to illustrate the concepts and equations developed above.

4.4.1 System description

The method for storage-dependent head is applied to a relatively small reservoir with a capacity of 75 TAF and the storage-head curve shown in Fig.4.6. The curve can be approximated analytically. At very low storage values the relationship is linear. For the rest of the storage range, the curve can be approximated by a quadratic polynomial. The power house is 50 ft below the reservoir.

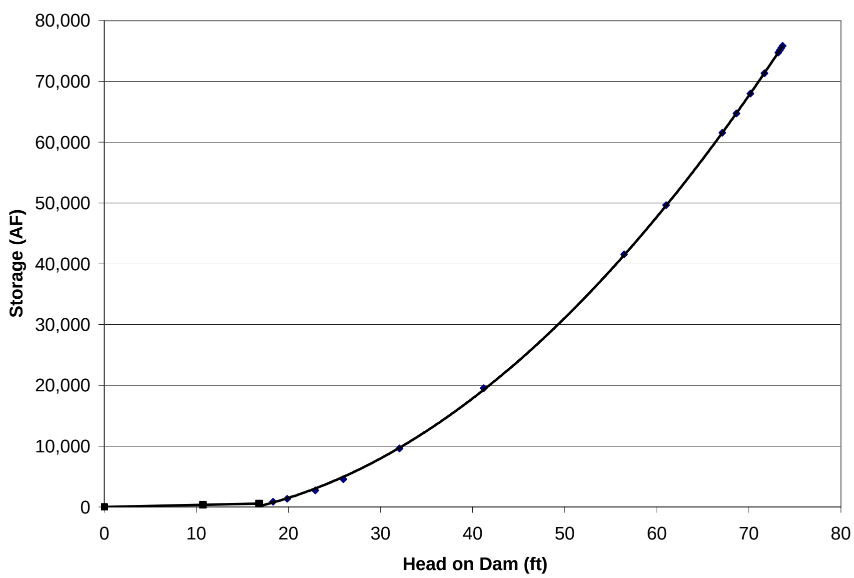

Figure 4.32: Storage-head curve for example application

Two different weeks will be considered to test the method: one in winter (10th week of the calendar year) and the other in summer (30th week of the year). Table 4.1 summarizes the information used in this example. Based on historical records for the California Sierra Nevada, for the summer week the net inflow (inflow minus losses) is set to zero. This means that losses, mainly due to evaporation offset the likely small natural inflows entering the reservoir. Initial storages are about 13% and 47% of storage capacity for weeks 10 and 35, respectively.

Hourly energy prices for the year 1999 were obtained from the California PX data (available at http://www.ucei.berkeley.edu/). The corresponding Price Duration (PD) and

Moving Average (MA) curves are shown in Fig. 4.6 at 5% frequency intervals. The "exact" MA for each percentile was calculated from the actual sample of prices. The "approximated" MA is obtained directly from the PD curve by averaging the corresponding price percentiles at 5% intervals. This approximation can result in errors of about 10% with respect to the exact MA.

Table 4.1: Summary of data

Storage Capacity (TAF)	75	
Turbine Flow Capacity (cfs)	1000	
Max. Release (TAF/week)	13.88	
	Week 10	Week 35
Initial Storage (TAF)	30	50
Net Inflow (cfs)	180	0
Average Price ($/MWh)	17.3	41.6

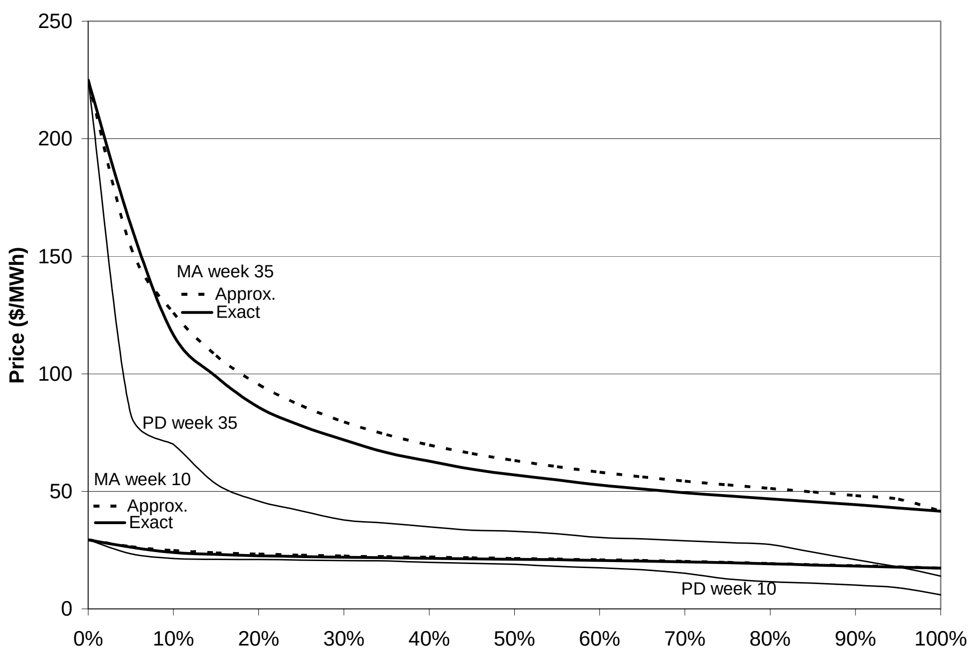

Figure 4.33: Price information year 1999 (Cal-ISO)

4.4.2 Approximation results without MIFs

The purpose is to estimate the optimal revenue during each week as a function of the initial and final storage, S_t and S_{t+1}, respectively, and the total volume of water allocated for generation during the week V_t. Storage information is necessary for head calculation.

For both weeks, the exact nonlinear optimization problem was solved using the CONOPT solver in GAMS, assuming perfect foresight of energy price and net inflow to the reservoir. For the proposed approximation, the total revenue for each week was calculated as described in section 4.3.2. The total revenues for each method are shown in Fig. 4.7 for the entire range of possible weekly release as a function of turbine capacity.

When the proposed method is applied using the actual sample MA, it matches the optimal results almost perfectly. With the approximated MA, the quality of the approximation depends on the week. As shown in Fig. 4.8, for week 10 the approximated MA is very close the exact one and therefore both revenues approximations almost coincide. For week 35, the errors introduced by approximating the MA result in a much worse approximation than that with the exact MA. The difference between the optimal and the estimated revenues increases with the total weekly release, reaching values as high as 10%. This is due to the greater price variability during week 35, having a much larger price range than week 10, as shown in the price duration curve in Fig. 4.7.

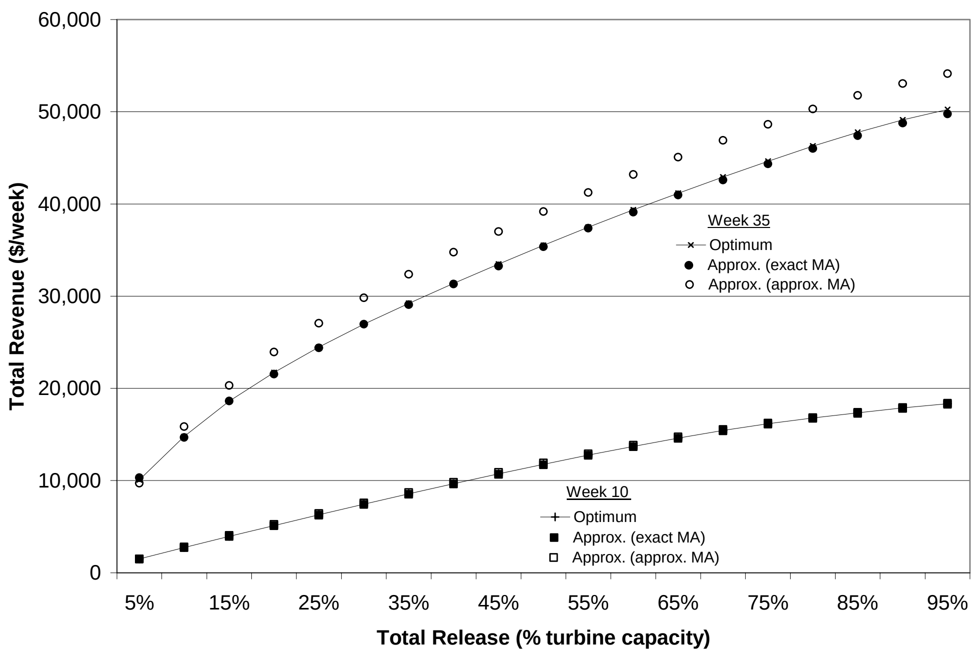

Figure 4.34: Effect of MA calculation on estimated revenues without MIF

4.4.3 Comparison with peak/off-peak price scheme

For comparison, we developed a method to design an optimal two-block (peak/off-peak) price scheme. A two-block price scheme will be optimal if the corresponding revenues have the least squared deviations from the optimal revenues for the whole range of total release. The design consists in finding the parameters P_{PEAK} , P_{OFF} , and f_{PEAK} as shown in Fig.4.1. Formally stated, the optimization problem is

$$\underset{P_{PEAK}, P_{OFF}, f_{PEAK}}{Min} \sum_{f_V} \left(B_{f_V}^{OPT} - B_{f_V}^{P/O} \right)^2$$

where the revenue calculated with the peak/off-peak structure is given by:

$$B_{f_V}^{P/O} = \begin{cases} \varepsilon \cdot \gamma \cdot \overline{h} \cdot C \cdot N \cdot P_{PEAK} \cdot f_V & f_V \leq f_{PEAK} \\ \varepsilon \cdot \gamma \cdot \overline{h} \cdot C \cdot N \cdot \left(P_{PEAK} \cdot f_{PEAK} + P_{OFF} \cdot (f_V - f_{PEAK}) \right) & f_V > f_{PEAK} \end{cases} \tag{4.13}$$

This problem requires a three-dimensional search. However, a condition can be imposed that relates the peak price P_{PEAK} and the frequency f_V, namely that the peak price matches the moving average price at that frequency, i.e. $P_{PEAK} = \overline{P}\left(f_{PEAK}\right)$. With this condition, the search becomes two-dimensional. The optimal values found for each week are presented in Table 4.2. For both prices, the corresponding exceedance percentile in the price duration curve is included in parenthesis. For week 10, given the flatness of the duration curve, the obtained percentiles differ somewhat from the common definition of peak/off-peak prices. The percentiles seem higher than expected for both peak and off-peak price. This shows that the common definition used in this kind of pricing scheme approximation does not necessarily results in revenues being closest to the actual ones. No alternative design would give a better representation of actual revenues than the optimal one presented here.

Table 4.2: Optimal peak/off-peak price scheme
($/MWH and corresponding % of generation capacity)

Week	f_{PEAK}	P_{PEAK}	P_{OFF}
10	54%	21.02 (23%)	14.78 (73%)
35	16%	98.10 (4%)	34.70 (41%)

The revenues were calculated using (4.13) with the parameters from Table 4.2. Fig. 4.9 shows how the estimation based on the optimal peak/off-peak scheme compares to the optimal revenue and to the estimation obtained with our method. The results for an alternative two-block pricing, where the peak price is defined as the 5% exceedance percentile, the off-peak as the 50% percentile, and a frequency of 20%, are presented for comparison. The optimal two-block pricing scheme used the exact MA for estimating the peak price for each f_{PEAK}.

The results in Fig. 4.9 clearly show that our method, when applied with the exact MA, outperforms the peak/off-peak price approximation. Also, the optimized two-block pricing scheme is a better approximation than the standard two-block pricing. This was expected since the optimal design minimizes the deviation from the optimal revenues.

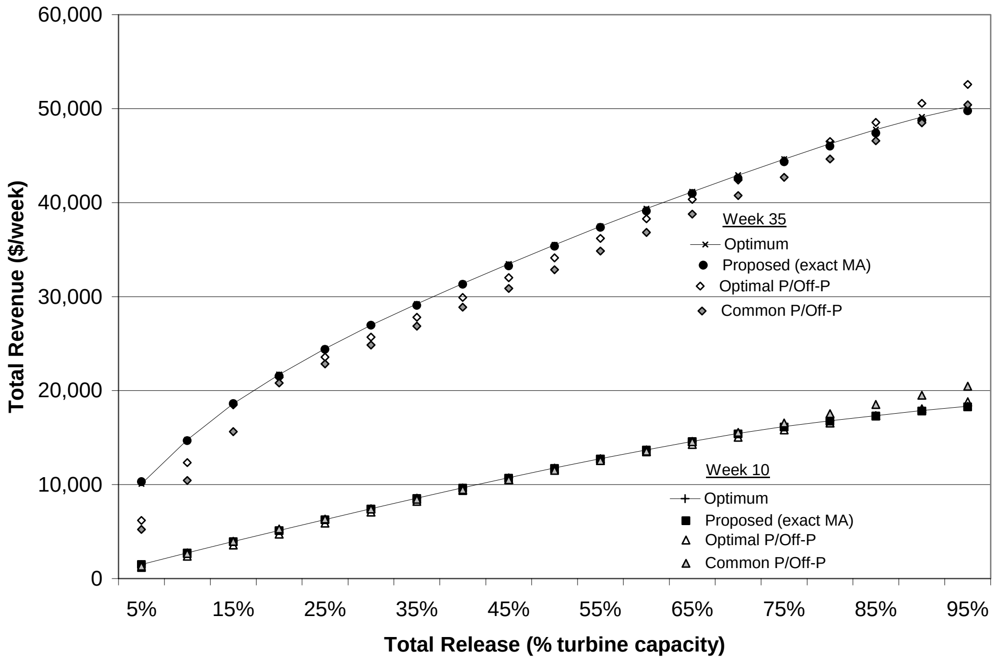

Figure 4.35: Comparison between the proposed method and two-block pricing approximation

A summary of the results, in the form of relative error, for the case without MIF appears in Table 4.3. The proposed method has the least error (less than 1%) when applied with the exact MA. The performance of the proposed method with the approximated MA depends on the week. For week 10, where the approximated MA is close to the actual MA, the proposed method still outperforms the two-block pricing scheme. Interestingly, for week 35, when applied with the MA approximated from the price duration curve at 5% intervals, this inexact implementation of the proposed method has more error than the two-block pricing. Both two-block pricing schemes use the exact MA; where the exact MA estimation is used, the proposed method has less error.

Table 4.3: Summary results without MIF

Method	Relative error	
	Week 10	Week 35
Proposed (exact MA)	0.4%	0.7%
Proposed (approx. MA)	0.9%	9.2%
Optimal Peak/Off-peak	2.5%	4.2%
Common Peak/Off-peak	5.8%	6.9%

4.4.4 Approximation results with MIFs

In general, MIFs decrease revenues by allocating more releases to hours with lower energy prices. We extended our approach to the cases with MIFs ranging from 5% to 50% of turbine capacity. The results are presented in terms of the ratio between the exact and approximated weekly revenue. In Fig. 4.10, each point corresponds to an average over the range of MIF requirements. Results are consistent with those without MIF. When applied with the exact MA, the proposed method approximates the optimal revenues within ± 1%. When a coarse approximation of the MA is used, errors can reach 7% for a week with high price variability like week 35.

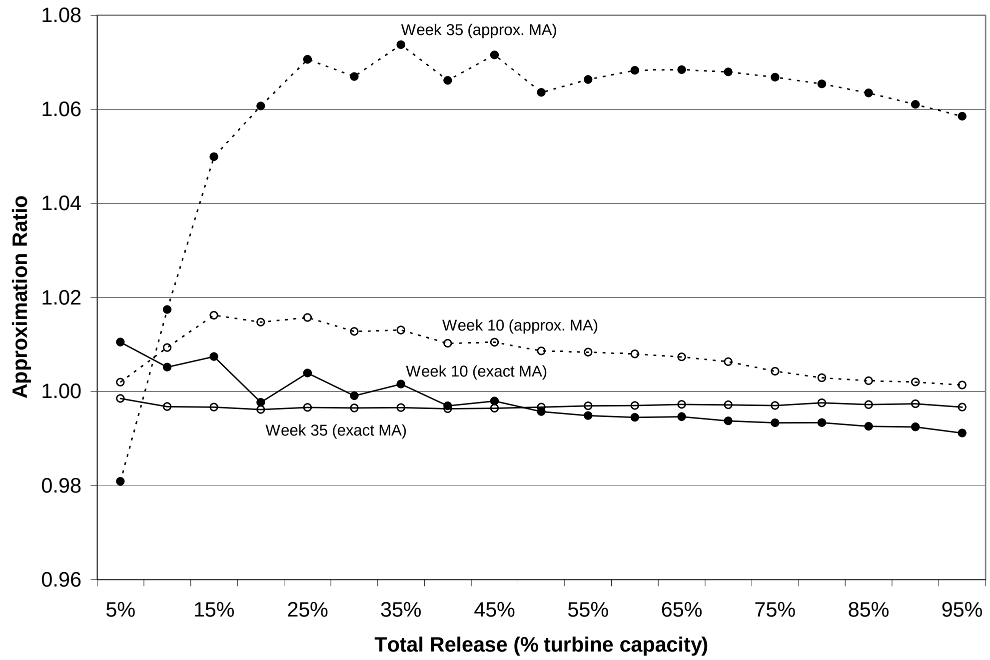

Figure 4.36: Ratio between approximated and optimal revenue (Average over MIF values)

Fig. 4.11 shows the average approximation ratios over total weekly water allocation for different levels of MIF. When the exact MA is used, our method underestimates the revenues by less than 1%. With MA approximated from the price duration curve at 5% intervals, the magnitude of the error depends on how close it approximates the exact MA. Again, the approximation for week 35 can be as large as 9% for small MIFs. In week 10 our method with approximated MA gives errors slightly higher than 1%. Interestingly, as the MIF requirement increases, the error due to the approximated MA decreases, reaching 3% and 0.5% for weeks 35 and 10, respectively. This can be explained from (4.12), where the benefit estimation is proportional to a weighted sum of the weekly average price and the MA price for the effective frequency. As the MIF increases, the weight on the MA price decreases and so its error has less influence on revenue estimation.

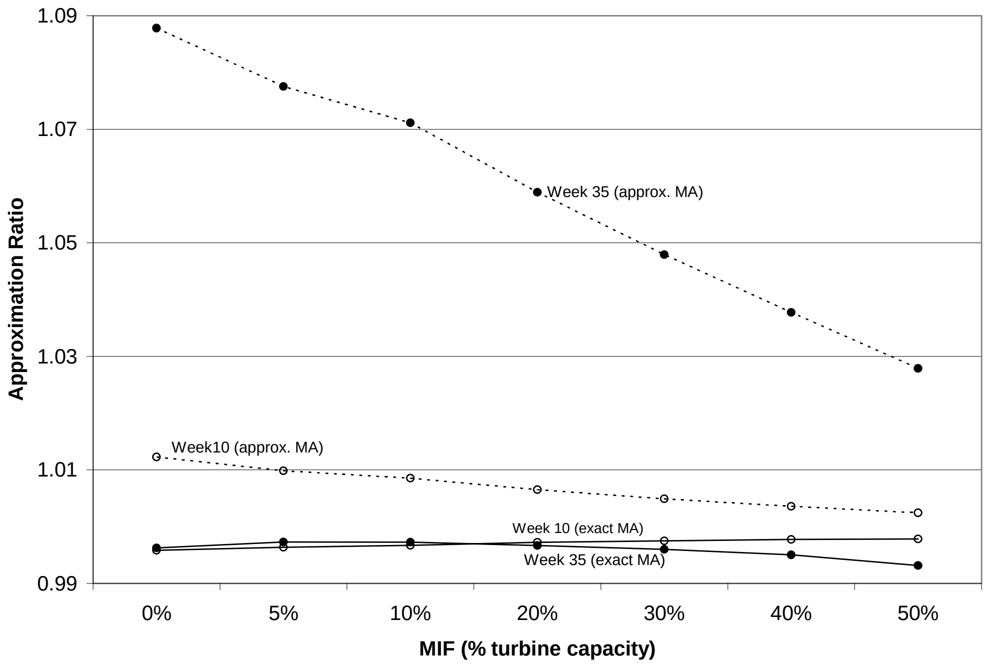

Figure 4.37: Ratio between approximated and optimal revenue (Average over total weekly releases)

4.5 Conclusions

A simple method is proposed to employ hourly price information to develop hydropower revenue functions for longer periods of time. The method is based on the hourly price duration curve and is meant to avoid the hourly optimization within longer-period scheduling or operational planning models. A key element of the method is the availability of a good estimate of moving average price over the duration range and perfect price forecasts one hour ahead. The method was applied to estimate the weekly revenues for two weeks, one in summer and the other in winter. With the exact MA, our method has errors smaller than 1% for both weeks. The exact MA can be closely matched with an approximation based on the duration curve at 1% intervals. When a coarser approximation of the MA is used, the errors increase considerably for the week in summer, which has a high price variation.

Our results were compared with the traditional two-block price structure approach. An optimal peak/off-peak price scheme was designed to minimize deviation from the optimal revenues. This optimal approximation results in relative errors of 2.5% and 4.2%, much higher than the 0.4% and 0.7% obtained with our method using the exact MA.

The method was extended for the case with environmental constraints in the form of minimum instream flows and for the case with storage-dependent head and storage varying over the operational period. Similar results were obtained.

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CHAPTER 5

HYDROPOWER RESERVOIR OPTIMIZATION WITH DOWNSTREAM TEMPERATURE MANAGEMENT

5.1 Introduction

The previous chapters evaluated the optimal operations of a hydropower reservoir incorporating basic environmental flow requirements on releases, expressed in terms of minimum flows and ramping rates during peaking operations. This present chapter introduces requirements on the temperature of reservoir releases. Release temperature control is an interesting problem for reservoir operations management during the summer, particularly for reservoirs with thermal stratification. Temperature plays a key role in stream ecosystem maintenance. Besides its direct effect on living organisms, it affects many physicochemical processes in the environment which define the quality of physical habitat available for species. Jackson *et al*. (2007) evaluated the effect of flow and temperature variations on invertebrate community structure, and found poor and uneven distribution in a regulated river as compared to an unregulated stream. Instream flow methods based on habitat suitability explicitly include temperature as a factor (Jowett, 1997). Cardwell *et al*. (1996) explicitly incorporate temperature effects on a habitat capacity index as part of a deterministic multiobjective analysis of water supply and downstream conditions for fish. Jager and Smith (2008) claim that water quality, considerably controlled by temperature, relates more strongly to fish health than hydraulic habitat, except for very low flows.

When fish live downstream the reservoir, the release temperature greatly affects the abundance and quality of fish. Warm water fish can be affected by cold water releases from the deepest portions of the reservoir. In the case of cold water fish, the problem is usually the early exhaustion of the cold water stored in the reservoir, what results in warm releases made through the rest of the season. Later in the summer, a combination of low flows and high temperatures leads to stress, particularly for salmonids and other cold water fish species. In both cases, selective withdrawal can be achieved by using a temperature control device (TCD). Optimal operations of selective withdrawal system for the deterministic case were studied by Fontane *et al*. (1981). This device allows selective choice of the temperature of water released from the reservoir.

This chapter includes development of an optimization model for the operation of a reservoir with a TCD. Release temperature control is aimed to support a cold water fishery during the summer under hydrologic uncertainty. A hypothetical application for a relatively small reservoir is included and results are analyzed in terms of operating policies, hydropower generation and revenues, and released temperature.

5.2 Preliminaries and model assumptions

Consider a two-layer stratified hydropower reservoir as shown in Fig.5.1. Water in the upper layer has a higher temperature than water in the lower layer. Releases for hydropower generation can come from either layer, or both. The temperature of the combined release is given by the simplified thermal balance:

$$T_{out} = \frac{T_U \cdot R_U + T_L \cdot R_L}{R_U + R_L} \tag{5.1}$$

where T_U and T_L are the water temperature in the upper and lower layer, respectively, and R_U and R_L are the releases from the upper and lower layer.

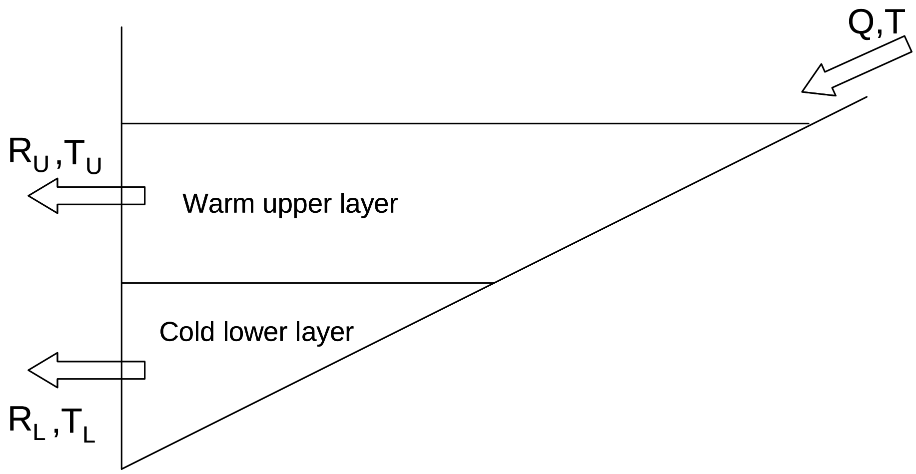

Figure 5.38: Schematic representation of a stratified reservoir

Releases have to comply with a maximum temperature target downstream. Depending on the particular system under study, the temperature at the point of interest can be affected by tributaries and local flows. To make this formulation as general as possible, it will be assumed that a maximum temperature target on the combined reservoir releases can be derived from the particular conditions. The problem consists of finding the optimal releases from each pool that maximize hydropower revenues and comply with the temperature requirement.

A detailed representation of the thermal dynamics in a stratified reservoir is fairly complex and beyond the scope of a hydropower planning model. Therefore, the following assumptions are considered:

A1) Temperature of releases from each layer is exogenous. This means that release decisions do not affect the temperature of water in each pool.

A2) The lower layer does not refill during the stratification season. This assumes that inflows to the reservoir are warmer than water in the cold water pool. Inflows refill the upper layer (warm water pool).

A3) Temperature in the lower layer is constant during the season, i.e. cold water does not warm during the summer.

A4) Water temperature in the upper layer increases linearly during the summer.

A5) Dynamics between layers can be represented by a deepening rate of the upper layer. This effect reduces the volume of cold water during the season augmenting the warm-water pool, even if no water is released from the cold water pool.

Given these assumptions, the temporal evolution of the storage of each pool during a period of length is defined by the following water balances:

Upper layer (warm water pool): $S_{t+1}^U = S_t^U + \left(Q_t - R_t^U\right) \cdot \Delta t + D_t$ (5.2)

Where:

S_{t+1}^{U} : storage content in the upper layer at the beginning of period t+1

Q_t : inflow rate to the reservoir during period t

R_t^U : release rate from upper layer during period t

D_t : volume associated with deepening of the warm pool during period t, which can be obtained from a deepening rate and the head-storage curve for the reservoir.

Lower layer (cold water pool): $S_{t+1}^{L} = S_t^L - R_t^L \cdot \Delta t - D_t$ (5.3)

Where:

S_{t+1}^{U} : storage content in the lower layer at the beginning of period t+1

Q_t : inflow rate to the reservoir during period t

R_t^U : release rate from lower layer during period t

D_t : volume associated with deepening of the warm pool during period t

The temperature of releases from each layer varies exogenously according to:

$$T_t^U = T_0^U + \gamma \cdot t \qquad T_t^L = T_0^L \tag{5.4}$$

Where T_0^U and T_0^L are the initial temperature of releases from the upper and lower pool, respectively. The warming of the upper layer is parameterized in terms of γ , a constant warming rate per time. A typical case for all relevant temperatures during the summer season is depicted in Fig. 5.2.

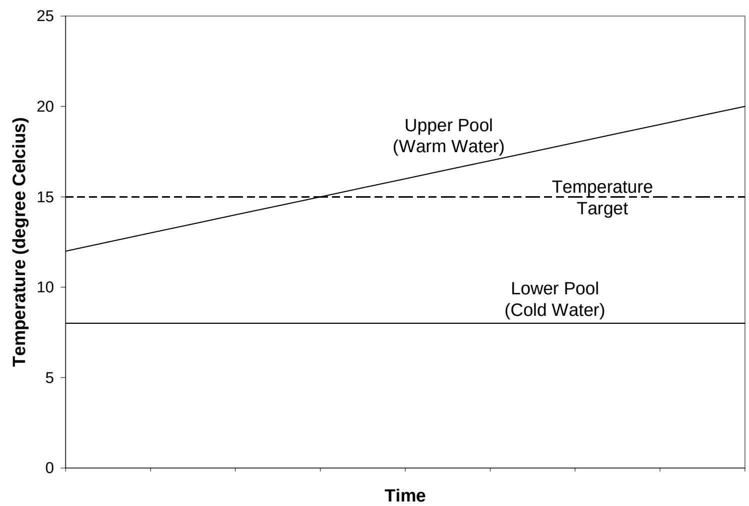

Figure 5.39: Temperature in the upper and lower layer compared to temperature target

Equations (5.2)-(5.4) describe the system at any point in time during the summer. In other words, all the information available to make release decisions is, for each pool, storage and temperature of releases.

5.3 Optimization formulation

In this section, the formulation of the optimization problem is developed in detail, including the definition of the objective, constraints and uncertain parameters.

5.3.1 Objective function

It is assumed that revenue maximization drives hydropower operations throughout the stratified season. If the season is divided into decision periods, the total revenue is the sum of revenues over these periods. Revenues in each period can be calculated using the expression (4.13) derived in chapter 4, which considers the effects of hourly-varying prices and minimum release requirement:

$$B = \left(E_V - E_{MIN}\right) \cdot \overline{P}_{EFF} + E_{MIN} \cdot \overline{P} \tag{5.5}$$

Where

E_{MIN} : energy generated with minimum release

E_V : total energy generation

$\overline{P}_{EFF}$: average energy price for energy during hours of peaking generation (higher than period average).

$\overline{P}$: average energy price during the period

The energy generated by a release R with head h during a period of length Δt can be calculated as:

$$E(R,h) = \varepsilon \cdot \gamma \cdot R \cdot h \cdot \Delta t \tag{5.6}$$

The total revenue over N periods is: $B_{TOT} = \sum_{t=1}^{N} B_t$ (5.7)

To avoid a myopic and unrealistic behavior in which the reservoir would be emptied at the end of the stratification season, an additional term representing the value of storage at the end of the season is included. Then, the non-myopic objective to be maximized is:

$$B_{TOT+END} = \sum_{t=1}^{N} B_t + V_{END}(S_{END}) \tag{5.8}$$

Estimating the carryover storage value is a difficult task that often relies on significant assumptions. The carryover storage value for a water supply reservoir has been studied extensively, ranging from a multireservoir study by Gal (1979) to a more recent analytic study by Draper and Lund (2004). Since in this case the only purpose of the carryover storage value is to avoid empting the reservoir at the end of the season, one way to proceed would be a trial-and-error approach in which a reasonable functional form for the value of ending storage is calibrated until it produces the desired effect of the resulting ending storage. Economic theory establishes that the value of a stock should have decreasing marginal returns, particularly if the value in each period, in this case hydropower revenue, is a concave function.

In the case of hydropower reservoirs, it is customary to use the value of the potential energy equivalent as a proxy for carryover storage value. This approach, however, poses some technical problems and does not represent the condition of decreasing marginal returns for the value of a resource stock. Considering variable head, the total energy stored in a reservoir can be calculated as the integral of the power generated at each reservoir storage level while draining the reservoir up to the minimum storage. Mathematically, the total potential energy associated with a storage level $\overline{S}$ is:

$$E(\overline{S}) = \int_{S_{MIN}}^{\overline{S}} \varepsilon \cdot \gamma \cdot h(S)\, dS$$

Where ε and γ are the powerhouse efficiency and the specific weight of water, respectively. Since the head increases with storage, the energy stored is a convex function of the water storage. More formally, after applying the Leibniz's rule to calculate the first derivative, the second derivative of the energy as a function of stored water is $E''(\bar{S}) = \varepsilon \cdot \gamma \cdot h'(\bar{S})$, which is strictly positive since head strictly increases with storage.

The economic value obtained as the product of stored energy times a single energy value is also a convex function. Therefore, this approach would result in a carryover storage value with increasing marginal returns. Moreover, if a nonlinear optimization technique is to be used, the resulting objective function can be non-concave and therefore have local optima. This can prevent the algorithm from finding the global optimum of the problem. The origin of this problem is that a single unit value is considered for all the energy stored in the reservoir. With variable energy prices, not all the energy is sold at the same price.

The carryover storage value can be derived more rigorously and economically by considering the infinite horizon problem of determining the value of water for all seasons in the year, one of these coinciding with the stratified season. This procedure, called value iteration relies on dynamic programming, and solves the optimization problem sequentially for several years until the value of water storage converges.

For the value iteration component of the model, the year was divided in three periods: pre-stratification, stratification, and post-stratification. The objective is to maximize total hydropower revenues in the steady state defined by the convergence of the economic value of reservoir storage over the years. Decisions in this model are total water release from the reservoir in each of the three periods. No distinction is made regarding temperature of releases since it can be assumed that no year-to-year relationship exists regarding the stratification of the reservoir. In other words, the proportion of warm and cold water at the end of the stratification period in one year does not affect stratification next year. Bartholow *et al*. (2001) found that for Shasta Lake in California, the total annual carryover storage influences the reservoir thermal structure more strongly than the use of a TCD. Nickel *et al*. (2004), performed a statistical analysis of the causes of reduced cold water storage in Shasta, and found that cold water storage during spring and early summer were negatively correlated with the hypolimnetic releases during late summer in the previous year. This year-to-year correlation can be explained by the large storage capacity of Lake Shasta, which allows for interannual regulation. The present study focuses on smaller reservoirs, without year-to-year correlation of reservoir thermal structure.

The problem is solved through a nested optimization procedure. First, the value of storage at the end of the stratification season is estimated via value iteration and then the intra-season problem is solved for the stratification season using the carryover storage value previously obtained. This two-step sequence is shown schematically in Fig.5.3.

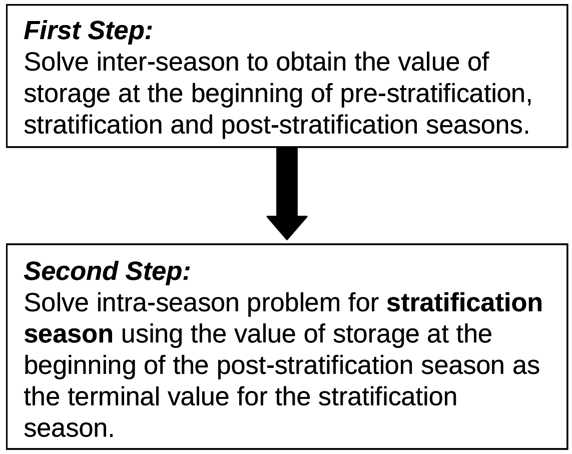

Figure 5.40: Inter- and intra-season problem sequence

5.3.2 Constraints

Several restrictions define the feasible range of releases from each layer of the reservoir during each time period. Constraints due to physical infrastructure limits include reservoir storage capacity and turbine flow capacity. Operational constraints include minimum required levels of storage and environmentally related requirements like minimum releases and maximum release temperature. The problem is also constrained by water balance in each layer and the entire reservoir. Each of these constraints can be mathematically represented by an equation or an inequality for each decision period t:

Water balance for the upper and lower layer is represented by Eqs. (5.2) and (5.3), respectively.

Maximum total storage level: $S_t^U + S_t^L \leq S_{MAX}$ (5.9)

Minimum total storage level: $S_t^U + S_t^L \geq S_{MIN}$ (5.10)

Maximum total release: $R_t^L + R_t^L \leq R_{MAX}$ (5.11)

Minimum total release: $R_t^L + R_t^L \leq R_{MIN}$ (5.12)

Maximum combined release temperature: $\dfrac{T_t^U \cdot R_t^U + T_t^L \cdot R_t^L}{R_t^U + R_t^L} \leq T_{MAX}$ (5.13)

5.3.3 Uncertainty

Several uncertainties are present in the problem, the most relevant being the amount and temperature of inflows to the reservoir, and energy prices. Other potential sources of uncertainty include weather and mixing conditions in the reservoir, which determine the stratification structure. An accurate representation of the stratification dynamics, including uncertainty, is beyond the scope of this work and therefore a deterministic approximation is used. The temperature of water released from each layer will vary exogenously as presented in Eq. (5.4) and is considered a parameter of the problem. Uncertainty in energy prices will be dealt with as presented in Chapter 4, which assumes the operator knows the price duration curve for energy and can make peaking decisions accordingly. For this formulation, the only source of uncertainty that will be explicitly modeled, i.e. considered as a random variable, is the inflows to the reservoir at each decision period, Q_t. Specifically, the probability distribution of inflows will be represented by the empirical distribution defined by an ensemble of inflows. Each inflow sequence represents a possible hydrologic scenario. Using an implicit stochastic approach, the optimization will be solved for each scenario. An explicit stochastic version of the model is currently under development.

5.3.4 Formulation as a mathematical program

All the above aspects of the formulation can be summarized in the following set of equations, which is called a mathematical program. The decision variables of the intra-season problem are the releases from each pool at each time period during the stratification season. The objective function is to maximize the average value of total revenues over M hydrologic scenarios plus the terminal value of storage. Q_t^m is the inflow in period t under the hydrologic scenario m.

$$\underset{R_t^{U,m},R_t^{L,m}}{Max} \frac{1}{M}\sum_{m=1}^{M}\left\{\sum_{t=1}^{N}\varepsilon\cdot\gamma\cdot(R_t^{U,m}+R_t^{L,m})\cdot\Delta t\cdot h_t + V_{END}(S_{END})\right\}$$

$$\begin{aligned}
s.t.\quad & S_{t+1}^{U,m} = S_t^U + \left(Q_t^m - R_t^{U,m}\right)\cdot\Delta t + D_t && \forall\ t=1,...,N \quad \forall m\\
& S_{t+1}^{L,m} = S_t^L - R_t^{L,m}\cdot\Delta t - D_t && \forall\ t=1,...,N \quad \forall m\\
& S_t^{U.m} + S_t^{L,m} \le S_{MAX} && \forall\ t=1,...,N \quad \forall m\\
& S_t^{U,m} + S_t^{L,m} \ge S_{MIN} && \forall\ t=1,...,N \quad \forall m\\
& R_t^{L,m} + R_t^{L,m} \le R_{MAX} && \forall\ t=1,...,N \quad \forall m\\
& R_t^{L,m} + R_t^{L,m} \le R_{MIN} && \forall\ t=1,...,N \quad \forall m\\
& \frac{T_t^U\cdot R_t^{U,m} + T_t^L\cdot R_t^{L,m}}{R_t^{U,m}+R_t^{L,m}} \le T_{MAX} && \forall\ t=1,...,N \quad \forall m\\
& R_t^{U,m}, R_t^{L,m}, S_t^{U,m}, S_t^{L,m} \ge 0 && \forall\ t=1,...,N \quad \forall m
\end{aligned}$$

The carryover storage value $V_{END}(S_{END})$ is obtained solving the mathematical program for the inter-season problem, which considers an infinite horizon and three periods per year. Decisions in this case involve total release from the reservoir during each season. The objective to be maximized is the discounted sum over an infinite number of years of the yearly hydropower revenue, which results from the aggregation of revenues in each season:

$$\underset{R_t}{Max}\ \underset{Q_t}{E}\left\{\sum_{YEAR=1}^{\infty}\beta\cdot\sum_{SEASON=1}^{3}\varepsilon\cdot\gamma\cdot R_{YEAR}^{SEASON}\cdot\Delta t\cdot h_{YEAR}^{SEASON}\right\}$$

Where β is an annual discount factor (less than 1).

The problem is subject to capacity constraints of storage and releases, and nonnegativity.

5.4 Solution Method

Both the inter- and intra-season problems are solved by implicit variants of sampling stochastic dynamic programming (SSDP), as suggested by Kelman *et al*. (1991). The present version does not consider a forecast or hydrologic state variable, and therefore the only (endogenous) state variables are total storage, and storage in the warm and cold water pool for the inter- and intra-season problems, respectively. The method consists of a backward solution of the Bellman equation (Kelman *et al*. 1991). For each time period, starting at the ending period, we solve the following optimization problem for a discrete set of state variables. In the inter-season problem, with the state represented by total storage S_t and decisions on total release under each scenario R_t^m, we solve:

$$\max_{R_t^m}\left\{\frac{1}{M}\sum_{m=1}^{M} B_t(R_t^m, S_t, S_{t+1}^m) + \beta \cdot f_{t+1}^m(S_{t+1}^m)\right\} \tag{5.14}$$

Note that this implicit stochastic version is equivalent to solving *m* separate deterministic problems, one for each hydrologic scenario. It assumes perfect hydrologic foresight by the operator.

Given the optimal set of releases R_t^{m*} that solve (5.14), the value function is updated for each scenario separately: $f_t^m(S_t) = B_t(R_t^{m*}, S_t, S_{t+1}^m) + \beta \cdot f_{t+1}^m(S_{t+1})$

Where $B_t(R_t^{m*}, S_t, S_{t+1}^m)$ is the revenue achieved in period t for an initial storage S_t, and optimal release R_t^{m*} under scenario m, and $f_{t+1}^m(S_{t+1})$ is the future value function, which represents the economic value of starting period $t+1$ with a storage S_{t+1} under inflow scenario m. This value is discounted by a factor β to account for intertemporal preferences by the decision maker. This version differs from the one suggested by Kelman *et al*. (1991) in that we obtain a different release for each inflow scenario, whereas the original version calculated a single target release for a relaxed version of the problem (without reservoir storage bounds), and then calculated the “actual” release by adjusting for feasibility. In that sense, the present version of the model employs an implicit stochastic approach.

Here, at each time period, given an initial storage we obtain the set of releases that optimizes the average over the inflow scenarios of the sum of immediate benefits (hydropower revenue) and future value associated with the resulting storage at the end of the period, which is the initial storage for the next period.

A well known drawback of dynamic programming techniques is the exponential increase of the computational burden with the dimensionality of the problem, what Bellman (1962) called the curse of dimensionality. Numerous approaches have been explored to alleviate the computational burden, including aggregation of states (e.g. Turgeon and Charbonneau, 1998), and approximation of the value function based on Benders decomposition (Pereira and Pinto, 1985).

In the traditional discrete DP approach, both decisions and states are discretized. For each discretized state, optimization is achieved using a discrete search procedure over decision space. This procedure normally requires some kind of interpolation of the future value function between discrete states. This approach has several problems. Besides the well known limitations related with dimensionality, it introduces significant interpolation errors if the state discretization is not sufficiently fine. The basic idea DP with value function approximation is to avoid discretization of the decision space and alleviate the discretization of the state space. With this approach, the optimal decision vector for selected state nodes is obtained in general by nonlinear programming techniques.

More recently, diverse forms of continuous approximations of the value function have been explored. Sharon *et al*. (1993) demonstrated the superior performance of cubic spline interpolation over tensor product linear interpolants with application to a multi-reservoir system. The present work employs a continuous approximation of the value function using Chebyshev polynomials, a family of orthogonal polynomials, as suggested by Howitt (unpublished manuscript). Judd (1998) shows that approximations based on Chebyshev polynomials outperform splines with the same number of parameters for smooth and regular functions. Moreover, when approximating a concave function with a singular point, only Chebyshev polynomials preserve concavity (Judd, 1998 pp. 229). This concavity-preserving feature is crucial to find the global optimum when nonlinear optimization methods are to be used. For the inter-season problem, where the state of the reservoir is represented by total storage, the problem reduces to a one-dimensional approximation of the value function.

The algorithm for the inter-season problem, based on value iteration of SSDP with Chebyshev approximation of the value function, is schematically presented in Fig.5.4, modified from Howitt (unpublished manuscript). The discrete values of storages at which the optimality equation is solved are carefully chosen to optimize the quality of the approximation. We use the so-called Chevyshev nodes (Judd, 1998 pp. 222). The main features of this node scheme are selected points are closer together towards the extremes of the feasible range and that the lower and upper bound are not included as nodes, the method selects very close points instead.

In the intra-season problem, the reservoir has two state variables, representing storage in the warm and cold water pool. The basic equation is an extended version of (5.14), with two storages and two releases. A limitation of multidimensional Chebyshev polynomial approximation, which is shared by all multidimensional approximation methods based on tensor product of one-dimensional approximations, is that it requires the function to be defined on a rectangular domain. In our case, the domain is not rectangular but triangular. More specifically, it is a simplex defined by the storage capacity constraint. To overcome this, the problem can be redefined by a change of variables. Instead of representing the state of the reservoir by upper and lower layer storage, we use total storage S_t and proportion of cold water to total storage $\alpha = S_t^L / S_t$. Storage in each pool can be calculated from these two state variables and therefore they contain the same information.

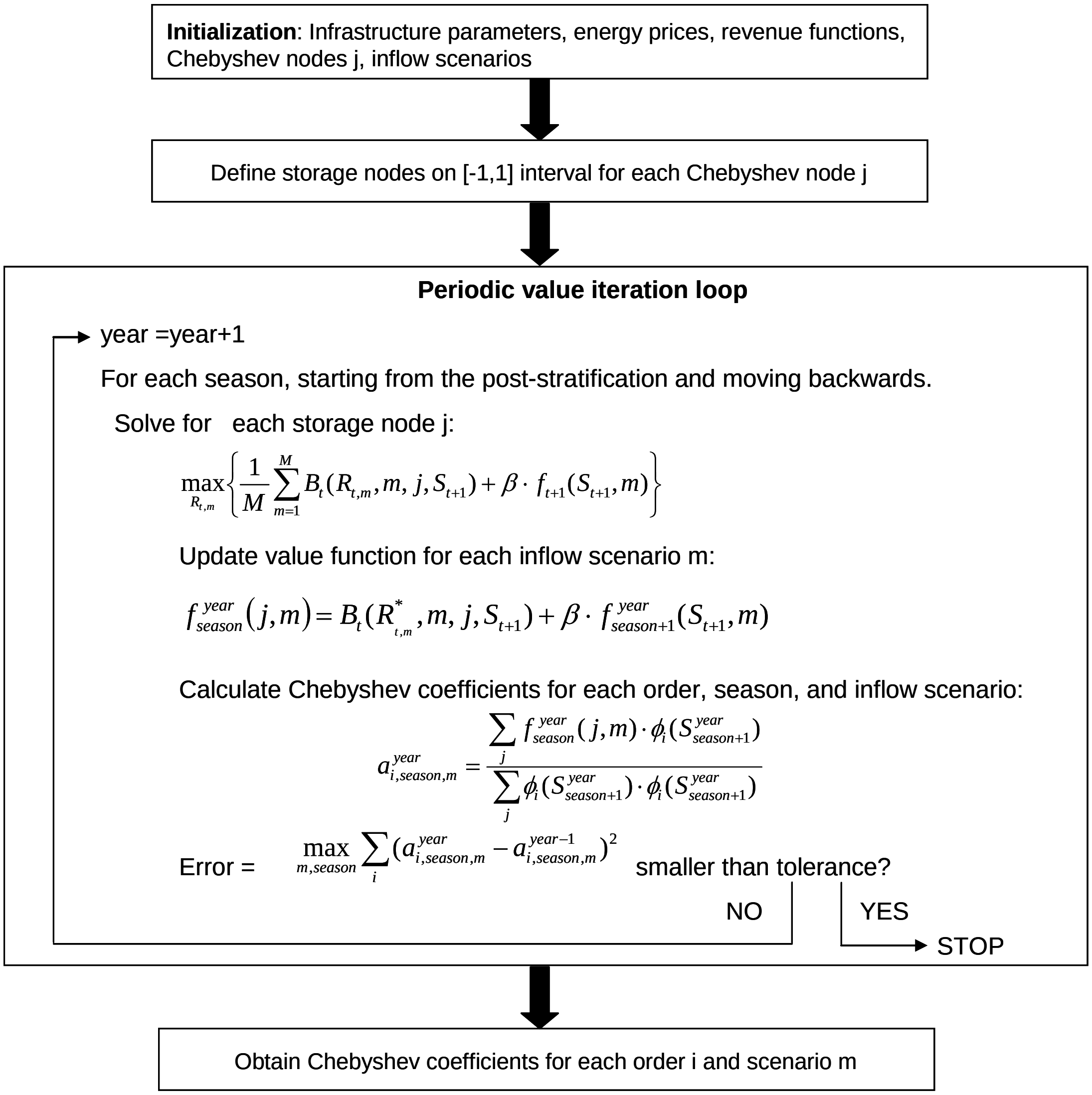

Figure 5.41: Inter-season algorithm

The new state variables define a rectangular domain for the value function, i.e. bounds for each one do not depend on the value of the other. These bounds are: $S_{MIN} \leq S_t \leq S_{MAX}$ and $\alpha_{t,MIN} \leq \alpha \leq 1$. The lower bound $\alpha_{t,MIN}$ for the proportion of cold water is obtained from the minimum volume of cold water available at a given period such that the minimum flow can be released at the target temperature and a minimum cold water volume is kept in storage for the next period. Such lower bound for feasible cold water storages is calculated recursively starting from the last period and includes the loss in cold water due to deepening of the upper reservoir layer. Then the minimum proportion α_{MIN} of cold water is obtained dividing the minimum volume by the lower bound on total storage. In reality, α_{MIN} depends on the value of storage and therefore the adopted approximation leaves a part of the feasible region out of consideration. This is a price paid for the requirement of a rectangular domain. More clearly, if the minimum feasible cold water volume at a given period is 1 TAF and the lower bound on total storage is 10 TAF, a value of α_{MIN} equal to 10% is adopted for all values of total storage. However, for a total storage of 100 TAF, the minimum feasible proportion of cold water is 1%. That portion of the feasible space, between 1% and 10% is not explored in this model.

5.5 Data for model application

This section includes an example application of the model to a hypothetical situation of a relatively small reservoir with a quadratic approximation of head-storage curve shown in Fig.5.5, modified from that of Lake Spaulding in the South Yuba system in the California Sierra Nevada. The values for the infrastructure parameters are presented in Table 5.1.

Table 5.4: Infrastructure parameters

Parameter	Symbol	Value	Units
Upper bound on storage	S_{MAX}	100	TAF
Lower bound on storage	S_{MIN}	10	TAF
Maximum release capacity	R_{MAX}	1000	CFS
Powerhouse efficiency	γ	0.8	N.A.
Base head	h_0	100	MTS

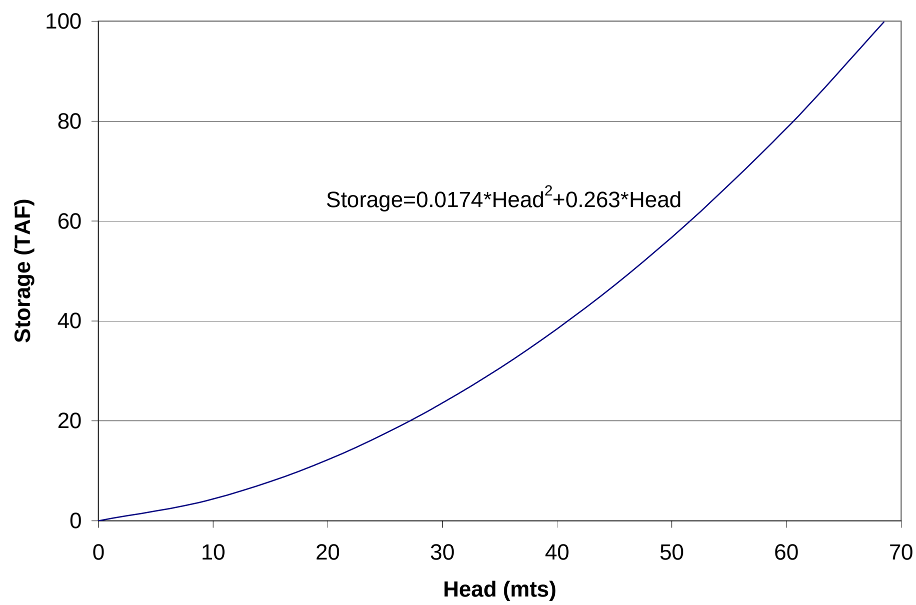

Figure 5.42: Head-storage curve for hypothetical reservoir

Inflows typically observed in the California Sierra Nevada during the period 1981-2005 form an ensemble of 25 scenarios. Energy price data will correspond to those observed in the year 1999 in California, obtained from the California Independent System Operator (Cal ISO).

5.5.1 Inter-season model

For the inter-season model, the year was divided into 3 seasons, pre-stratification (weeks 1-21), stratification (weeks 22-38), and post-stratification (weeks 39-52). The stratification period contains 17 weeks, roughly including the months of June to September. The inflow ensemble for the seasonal model is shown in Fig.5.6. Scenarios cover a wide range of hydrologic conditions.

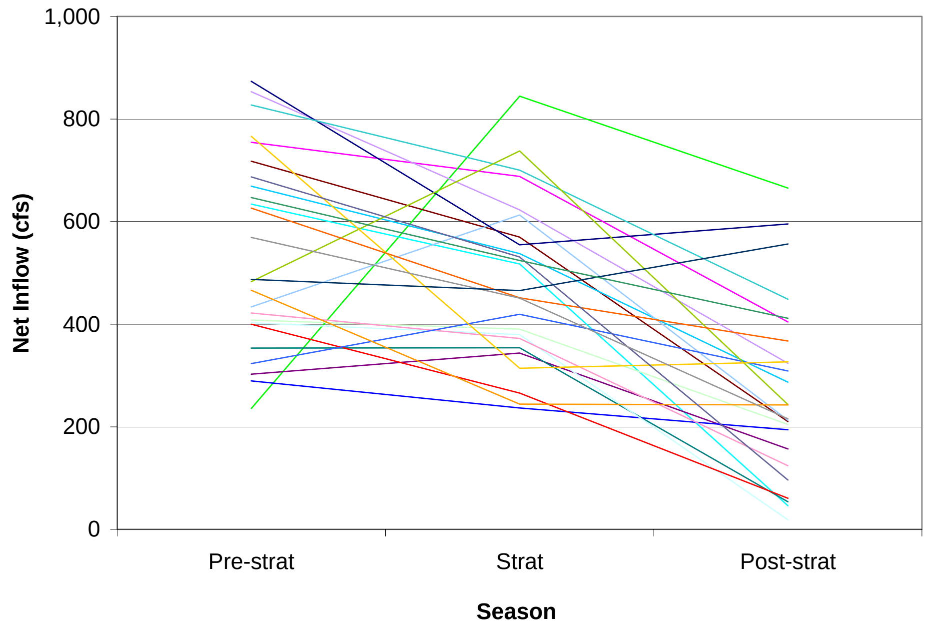

Figure 5.43: Net inflow ensemble for seasonal model

Energy price data are necessary for revenue calculation, as presented in the previous chapter. The relevant information is the curve of moving average (MA) prices as a function of the frequency of exceedance. These MAs correspond to the average of all hourly observed prices . Fig.5.7 shows the price frequency curves on which the MA curves shown in Fig.5.8 are based. The higher peak prices, at about 230 $/MWh, are observed during the stratification season (those with very small exceedance frequency), but the post-stratification season has higher prices for almost all frequencies. The lowest prices in the year are observed during the first 21 weeks (pre-stratification season), with a peak price of 50 $/MWh. From Fig.5.8, overall average prices, i.e. those at 100% exceedance frequency, are 25-45 $/MWh.

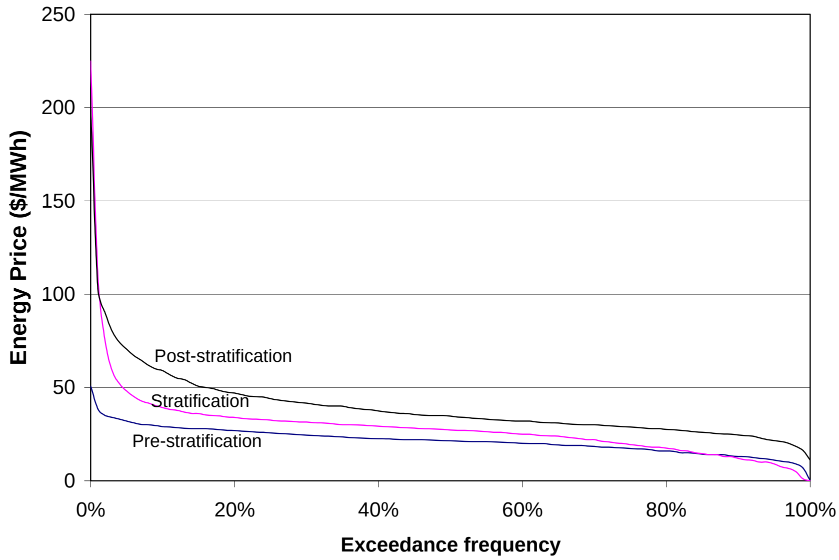

Figure 5.44: Price duration curve seasonal model

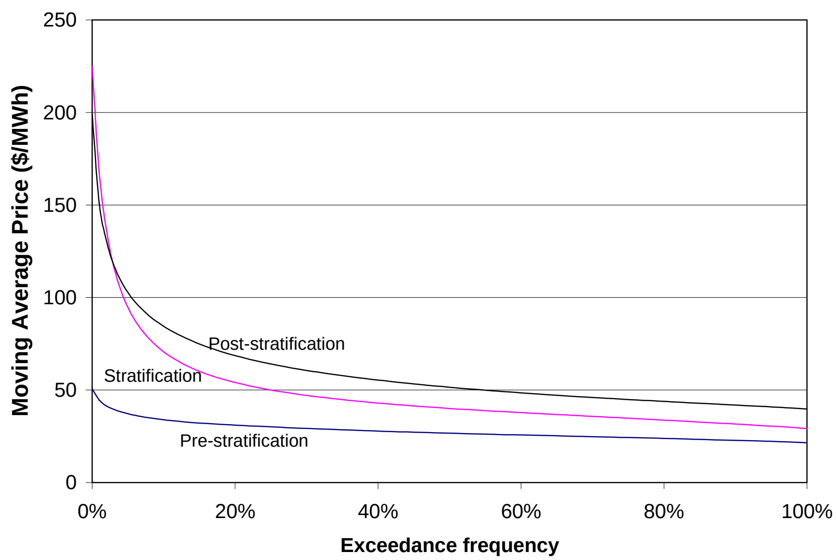

Figure 5.45: Moving average price seasonal model

Applying the algorithm in Fig. 5.4 we obtain the coefficients for each Chebyshev polynomial term. Initially, an approximation of order 5 was used, but results indicated that an order 3 would suffice for our purposes. The value function for the post-stratification season, which represents the carryover storage value for the end of the stratification season is shown in Fig. 5.9 for minimum required releases of 10, 50 and 100 cfs, equivalent to 1%, 5% and 10% of turbine capacity. As expected, the value of storage decreases as the minimum required release increases. The negative coefficient of the squared term indicates that the curves are concave, which was expected and necessary to ensure a global optimum in the intra-season problem. Since the nonlinear optimization methods for the stratification season are based on derivatives, it is the slope of the curve and not the absolute value what determines optimality. In fact, the condition for optimality, when no constraint is binding, is that the marginal values of current and future use of water are equal (Draper and Lund, 2004).

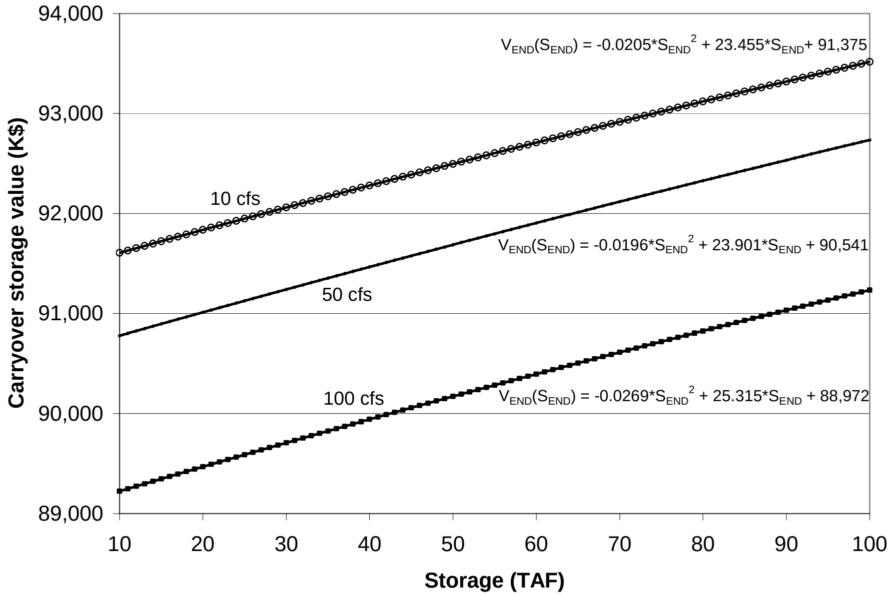

Figure 5.46: Carryover storage value for minimum required release of 10, 50, and 100 cfs

The effect of a minimum release requirement is clear in Fig.5.9. As the required release increases, the value of having a given amount of water stored in the reservoir decreases. The higher the minimum release the smaller the amount of water that can be used for peaking operations. More water is used for generation at every hour, even those with low prices. The marginal value of carryover storage S_{END} for each minimum release requirement is presented in Table 5.2, which shows the ranges for minimum and maximum storage:

Table 5.5: Marginal value of carryover storage

Minimum release (cfs)	Marginal Value ($/AF)	Range ($/AF)
10	$23.455 - 0.041 \cdot S_{END}$	19.36-23.05
50	$23.901 - 0.039 \cdot S_{END}$	20.00-23.51
100	$25.315 - 0.054 \cdot S_{END}$	19.92-24.78

5.5.2 Intra-season model with temperature management

The ensemble of 25 scenarios of weekly net inflow for each of the 17 weeks in the stratification season is shown in Fig. 5.10. The general trend, represented by the average (bold line), exhibits a decrease of inflows as the season progresses. Early in the season inflows are as large as 2,000 cfs (twice the turbine capacity) whereas by the end all scenarios are below 500 cfs. Also, the dispersion between scenarios decreases over time. Starting in week 8, some scenarios become quite dry.

For the exogenous representation of temperature dynamics, the lower layer will be at a constant temperature T_0^L of 8 °C. The starting temperature in the upper pool T_0^U will be 12 °C, with a warming rate γ equal to 0.5 degree per week. The temperature target will be set at 15 °C.

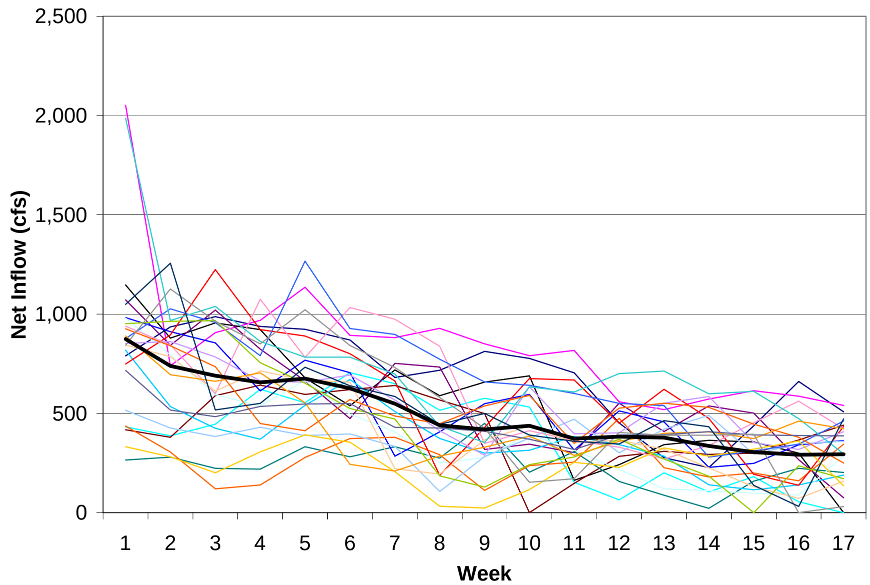

Figure 5.47: Net inflow ensemble during stratification season

Energy price data, represented by the price duration and moving average curves for each week in the stratification season, are presented in Figs. 5.11 and 5.12, respectively. The 4 curves with highest observed prices correspond to weeks 14, 13, 7 and 5. Prices curves during all other weeks are alike.

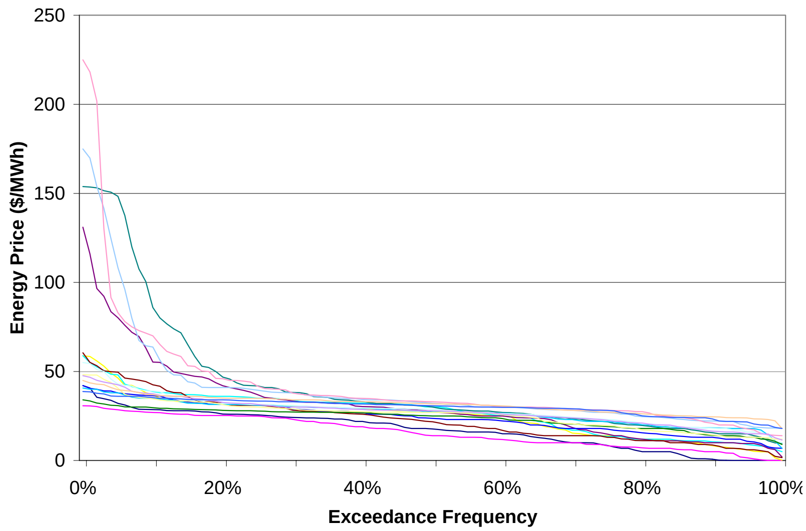

Figure 5.48: Price duration curve for each week during the stratification season

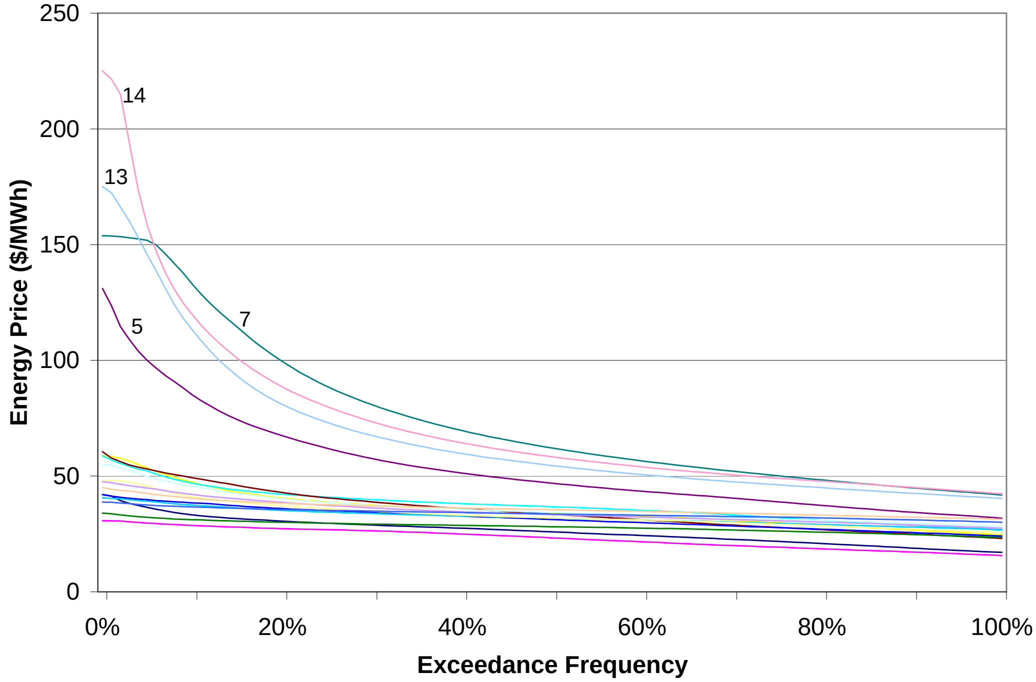

Figure 5.49: Moving average price for each week during the stratification season

5.6 Intra-season model results

Results for the optimal operation of the stratified reservoir during summer are obtained in two steps. First, a backwards SSDP recursion is performed to estimate the Chebyshev coefficients that approximate the total value of starting at selected combinations of total storage and proportion of cold water (see Fig.5.4). The discrete state points for the coefficient estimation are not equally spaced over the feasible range of each state variable. Nodes are defined using the Chebyshev rule (Judd, 1998 pp. 238), with a higher density of points close to the upper and lower bound of each state variable. The set of combinations is obtained as the tensor product of one dimensional Chebyshev nodes for each state variable. For each week, starting from the last, this step solves one optimization problem for each combination of states and stores the value of the objective function. After solving the optimization for all combinations of state variables in a given week, the coefficients of the Chebyshev approximant are calculated as shown in Fig.5.4.

Having a continuous approximation for the value functions for each scenario and week in the stratification season, the second step solves an optimization problem which maximizes the sum of immediate and future benefits at each week for equally spaced combinations of storage and proportion of cold water at regular intervals. This step includes a greater number of state combinations than used in the estimation phase.

Model results are scenario- and week-dependant. However, for our purposes we are interested in the average over the 25 scenarios. Results are shown for selected weeks, chosen by three criteria. First, as shown in Fig. 4.2, early in the season the temperatures of both pools are colder than the temperature target. Past a certain point (week 7 in this case), the temperature in the upper layer becomes higher than the target. We would expect to see differences in the results for weeks before and after week 7. A second criterion for selecting weeks is the energy price factor. Weeks with high and low prices have to be included to identify the price effect on the results. A third factor to consider is the effect of the value of the ending storage, which is expected to be stronger towards the end of the season. Based on these criteria, results are presented for weeks 1, 7, 10, 14, and 17. Table 5.3 includes price information for the selected weeks. Considerable differences in average energy price and prices at different exceedance levels are observed among the selected weeks.

Table 5.6: Energy price information for selected weeks

Week	1	7	10	14	17
Average	17.03	41.81	28.18	42.38	30.04
5%	32.09	148.35	42.80	82.93	36.04
25%	25.60	41.88	31.50	41.71	33.34
75%	8.49	21.71	23.02	28.22	28.12
95%	0.05	14.89	16.01	17.83	21.61

We are interested in both the economic and environmental performance of the system. Operational insights are also of interest. At the beginning of each week, the operator is faced with the problem of how much water to release from each reservoir pool to generate power. Immediate hydropower revenues are weighted against the value of the resulting warm and cold water storages for the next week. The economic performance of the system is herein represented by the energy produced and revenues obtained each week. Release temperature is used as a measurement of the environmental performance. Operational insights can be extracted from carryover storage (total and of cold water), releases (total, cold, and warm). The economic impact of minimum release and maximum temperature is studied through its respective marginal values.

In most cases, results will be presented as surfaces with the two horizontal axes representing levels of storage and proportion of cold water. The vertical axis will represent the result of interest. When surfaces were not clear, equivalent curve plots are presented instead.

5.6.1 Release temperature and thermal operations

As expected, release temperatures follow the temperature pattern of the upper (warm) pool until it reaches the maximum allowable temperature. From that point on, water is released at 15 °C, the maximum allowed. This is so for any combination of total storage and cold water content. Fig.5.13 shows the release temperature for each week.

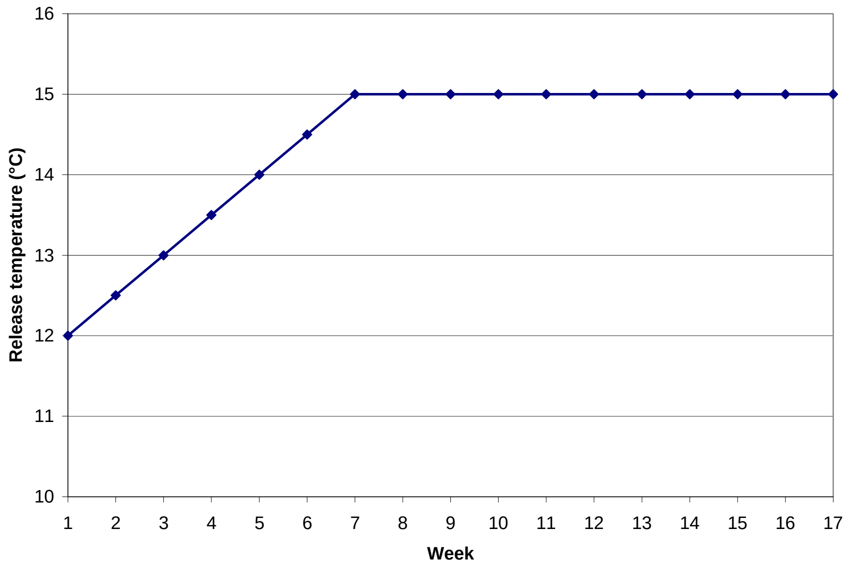

Figure 5.50: Average release temperature through the stratified season

This result indicates that, as expected, during the first 7 weeks only warmer (but still cool) water is released. Cold water is saved for the periods when the upper layer is warmer than 15 °C. Starting in week 8, cold water is released in amounts that are just enough for the mixed released to reach the maximum allowed temperature. An exception to this behavior, which is not reflected in the average shown in Fig. 5.13, occurs for cases when the reservoir is relatively full of cold water (no warm water is in storage), cold water can be released even when it is not needed for temperature purposes. This occurs in weeks with relatively high energy value (7 and 14), when the optimal hydropower release exceeds the inflow of warm water during the week in question. In those instances, release temperatures decrease to about 14.8 °C.

5.6.2 Release decisions

The operational decision at each week is how much water to release from each pool of the reservoir. Water can be released without running through the turbines into an alternative stream which is not sensitive to temperature. These releases will be called spills although they can happen even if the turbines are not running at flow capacity. The total release, which includes flow through the turbines and spill, is shown for weeks 1, 7, 10, 14, and 17, in Figs. 5.14 to 5.18, respectively.

A general trend observed in all selected weeks is that for all content of cold water, total release increases (or at least does not decrease) with total storage at the beginning of the week. This is expected since more water is available for generation. Interestingly, turbine flow capacity (1000 cfs) is never reached. Also, the maximum total release, which occurs when the reservoir is full, decreases as the season progresses. This is consistent with the decreasing trend in the inflows observed in Fig. 5.10. Some differences are observed between different weeks. For weeks 1, 10, and 17, only the minimum required is released for low storage values. This is due to the relatively low energy value during those weeks compared to weeks 7 and 14 (see Table 5.3), when even for low total storage releases exceed 150 cfs and 100 cfs, respectively. An extreme case is the last week of the season, when releases exceed the minimum required only when the total storage is higher than 90 TAF (90% of storage capacity). This is the combined effect of relatively low energy value and the lowest inflows in the season.

The effect of the amount of cold water stored in the reservoir at the beginning of each week varies depending on the week. For weeks 1 and 7, no evident effect is observed. This was expected because until week 7 the temperature of the upper pool does not exceed the maximum allowable temperature for the combined release. As mentioned in section 5.6.1, almost exclusively warm water is released during the first seven weeks of the season. In weeks 10 and 14, the effect of the cold water storage is clear. In both cases the total release drops abruptly when a very low amount of cold water is available. With the exception of very high total storages, the total release is 10 cfs, the minimum required.

This is explained because the lower bound considered for the content of cold water is the amount just needed to release the minimum flow at the adequate temperature. Total releases above 10 cfs for total storage values above 90 TAF (or 90% of storage capacity) with the minimum feasible content of cold water are explained because water is spilled. Although counter-intuitive to some extent, unproductive releases can occur even when turbine capacity is not exhausted. With little cold water available and high storage levels, the carryover storage reaches capacity and the extra available water cannot be released through the turbines, because the constraint on temperature would be violated. Thus, the extra water is spilled to the alternative reach, without economic value for generation but also without increasing the combined release temperature.

In week 14 (Fig. 5.17), besides the abrupt decrease in release as cold water content reaches its minimum, cold water content influences total releases at relatively high levels of cold water content (between 60% and 80% of total storage). In that week, energy value is high, so relatively large turbine releases would be in order. For total storage levels between 40% and 60% of storage capacity, total release decreases about 50 cfs when the cold water available drops from high to medium values. Again, a high release level cannot be sustained as the cold water content becomes limiting.

Interestingly, in the last week of the season (Fig. 5.18), no effect of the cold water content is observed on total releases. This contradicts intuition, since at the end of the season the upper layer is warmest and temperature would have been expected to limit releases. However, the contradiction is only apparent. During this week only the minimum is released except when the reservoir is near full. The lower bound on cold water storage ensures the appropriate temperature for minimum releases. For total storage above 90 TAF spills occur. As will be more clearly seen in the energy outcome of the system, only the minimum flow is passed through the turbines when the cold water content is lowest. The rest of the total release shown in Fig. 5.18 is released as a spill, without producing electricity.

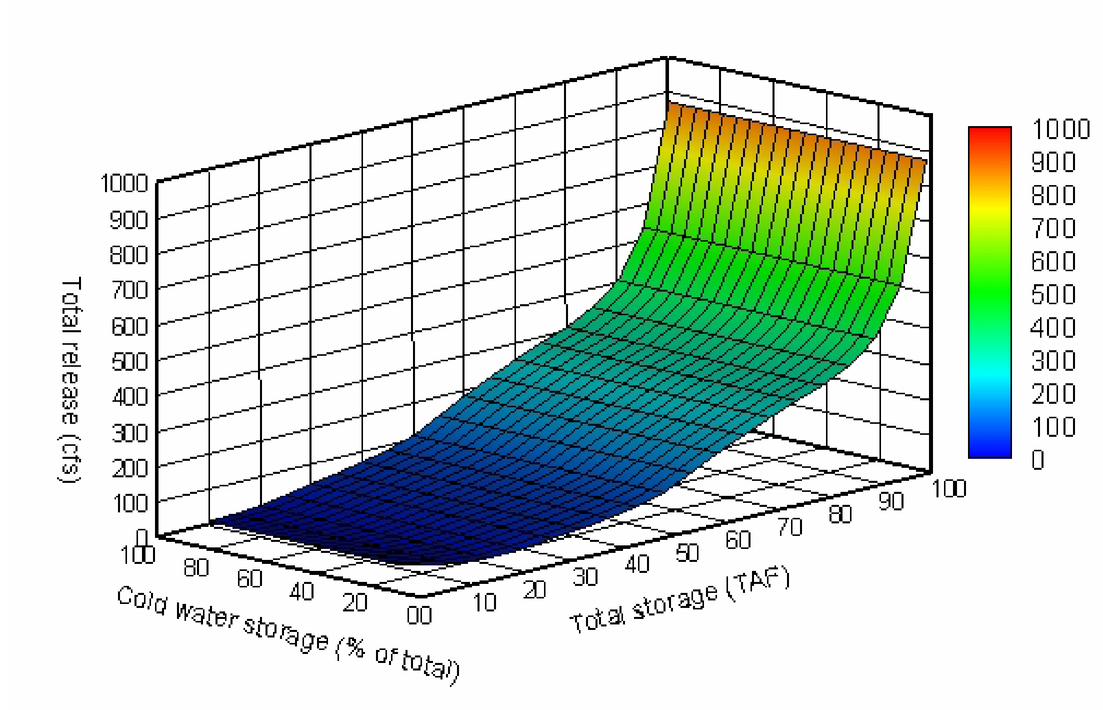

Figure 5.51: Total expected release in first week for minimum release of 10 cfs

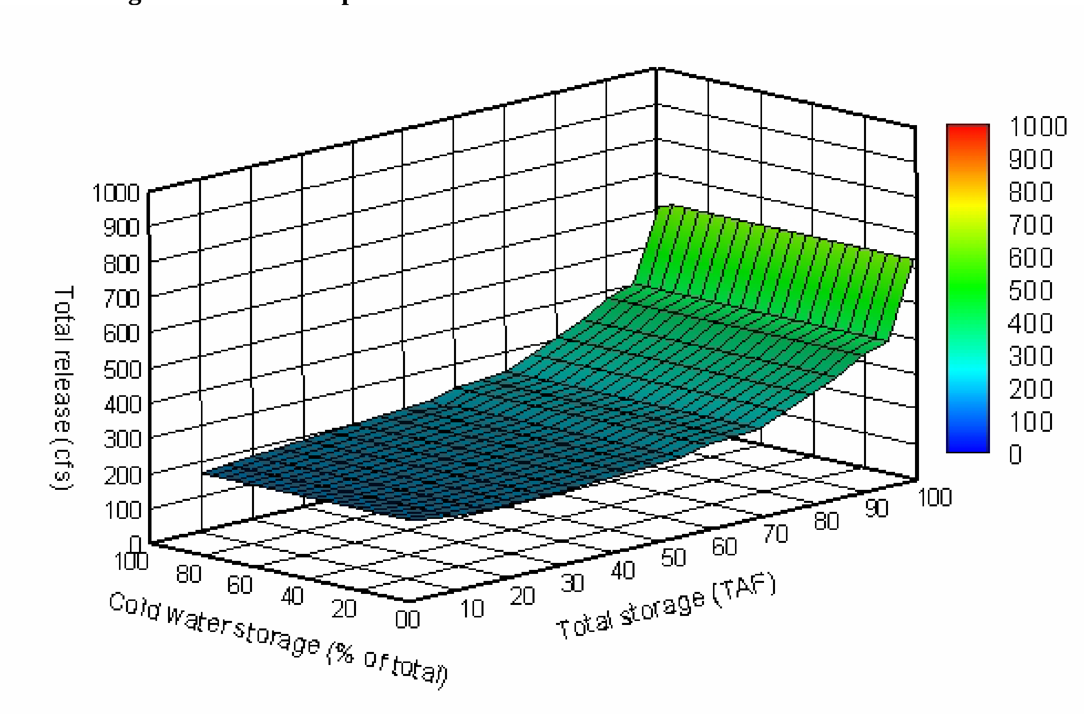

Figure 5.52: Total expected release in week 7 for minimum release of 10 cfs

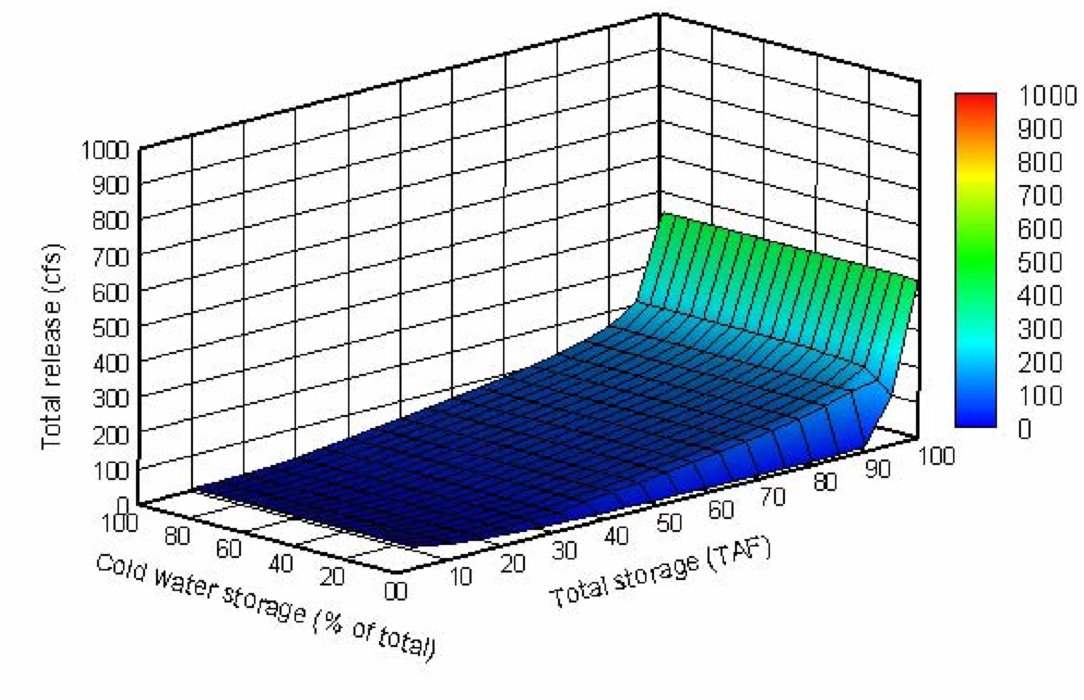

Figure 5.53: Total expected release in week 10 for minimum release of 10 cfs

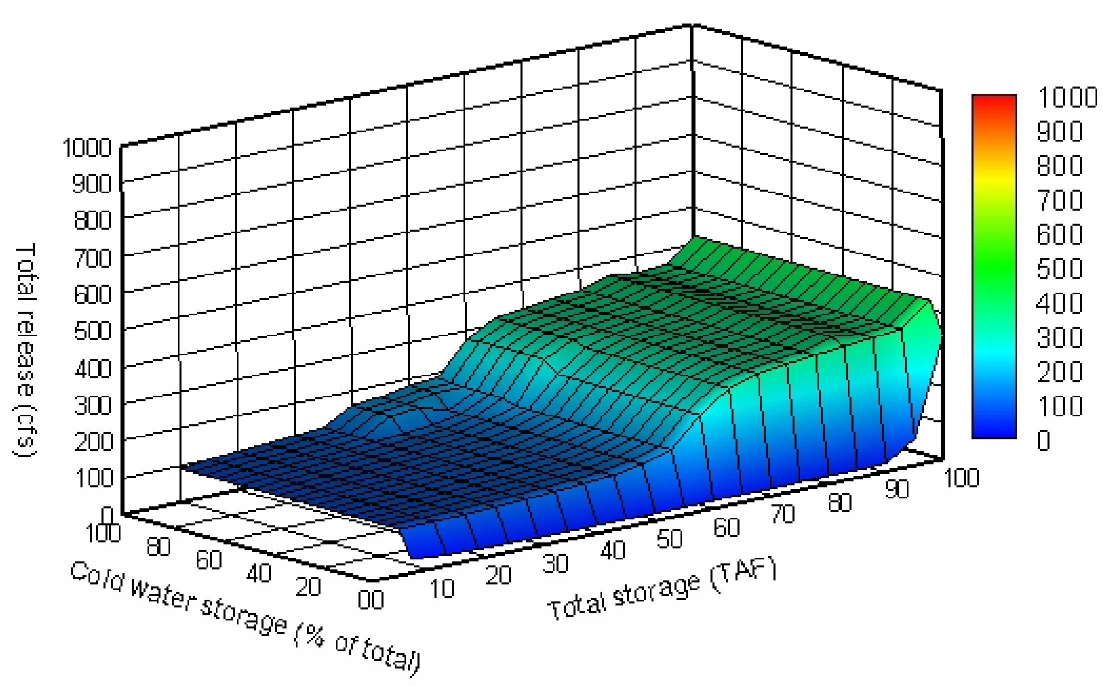

Figure 5.54: Total expected release in week 14 for minimum release of 10 cfs

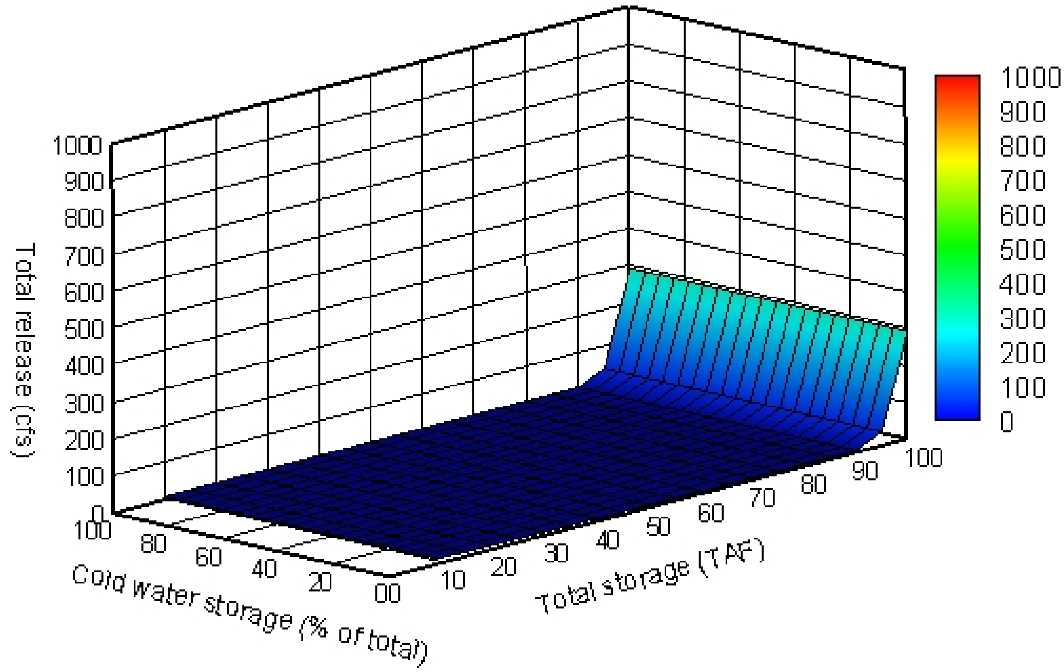

Figure 5.55: Total expected release in week 17 for minimum release of 10 cfs

5.6.3 Energy production

Energy is the direct economic good provided by hydropower plants and the only source of revenue considered in this study. Ancillary services, like capacity reserve, can be an additional important source of revenue but are not included in the present model. Energy output surfaces for the selected weeks are shown in Figs. 5.19 to 5.23. As expected, the energy surfaces follow the same pattern as the total release. Energy output increases with storage. Energy output for high storage values is highest early in the season, when the inflows are highest. Since total release includes spills, the influence of minimum cold water content as a limiting factor is clearer in the energy production, which reflects the release that contributes to revenues. For weeks 1 and 7, no effect of the cold water storage is observed. For weeks 10, 14 and 17, the total energy output drops to a minimum when the cold water content can only support the minimum release at 15 °C. In week 14, the effect of cold water content is not limited to the instances when cold water storage is the minimum feasible. For medium storage levels, energy output exhibits three levels. The highest energy production occurs for very high cold water contents. When the cold water content drops from high to medium, energy production decreases to an intermediate level. Finally, when the cold water available is the smallest possible, energy production experiences a sudden decrease to reach its minimum level.

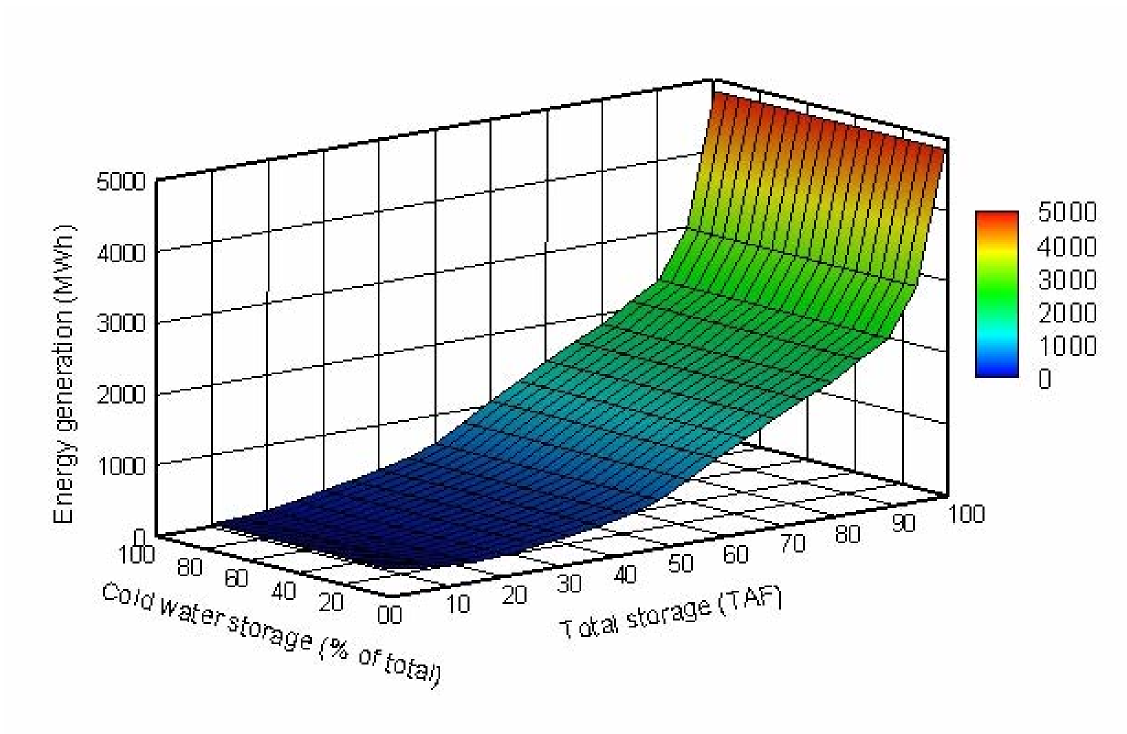

Figure 5.56: Expected energy production in the first week for minimum release of 10 cfs

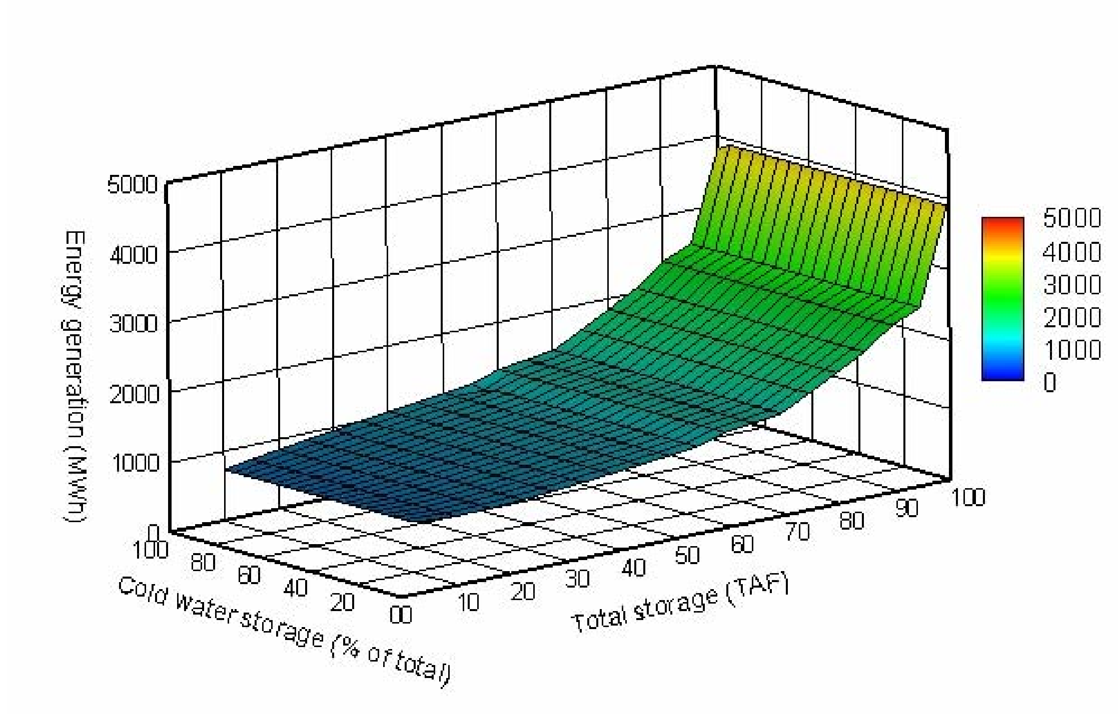

Figure 5.57: Expected energy production in week 7 for minimum release of 10 cfs

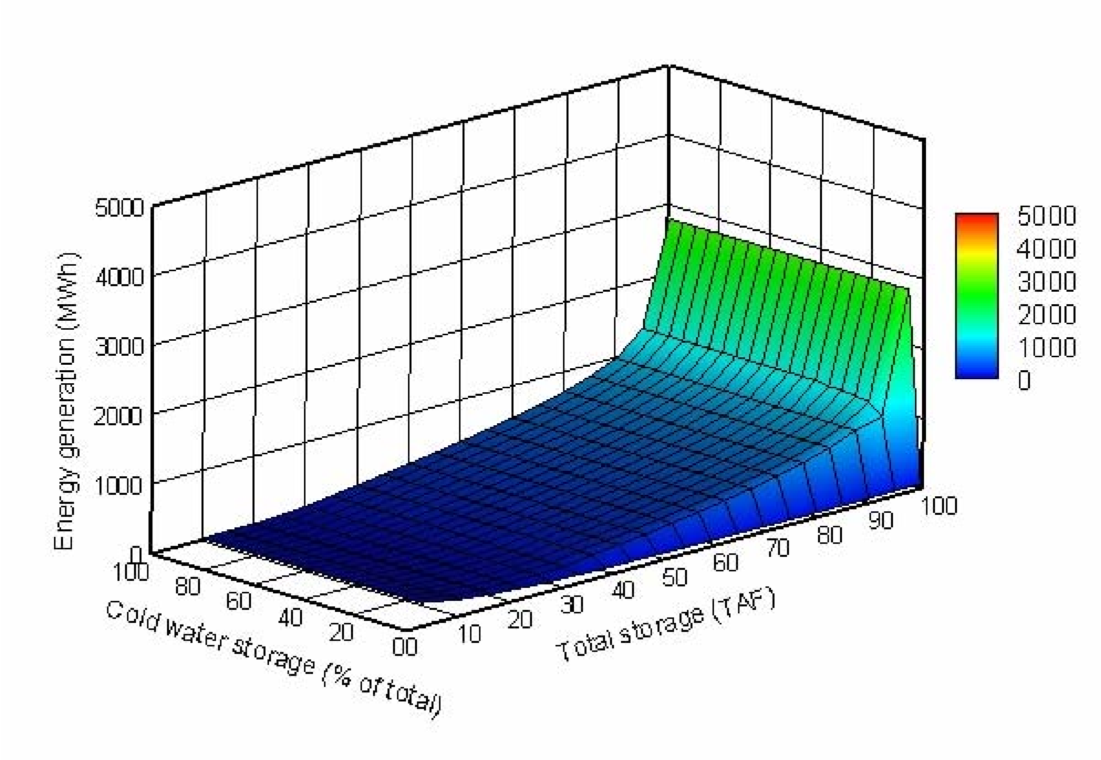

Figure 5.58: Expected energy production in week 10 for minimum release of 10 cfs

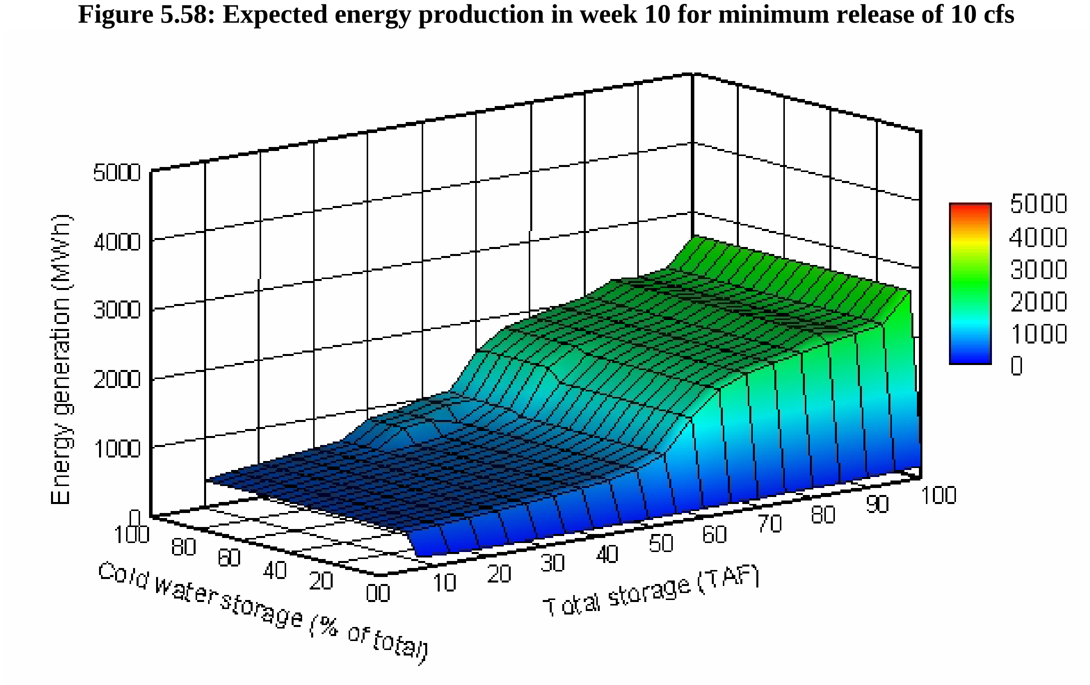

Figure 5.59: Expected energy production in week 14 for minimum release of 10 cfs

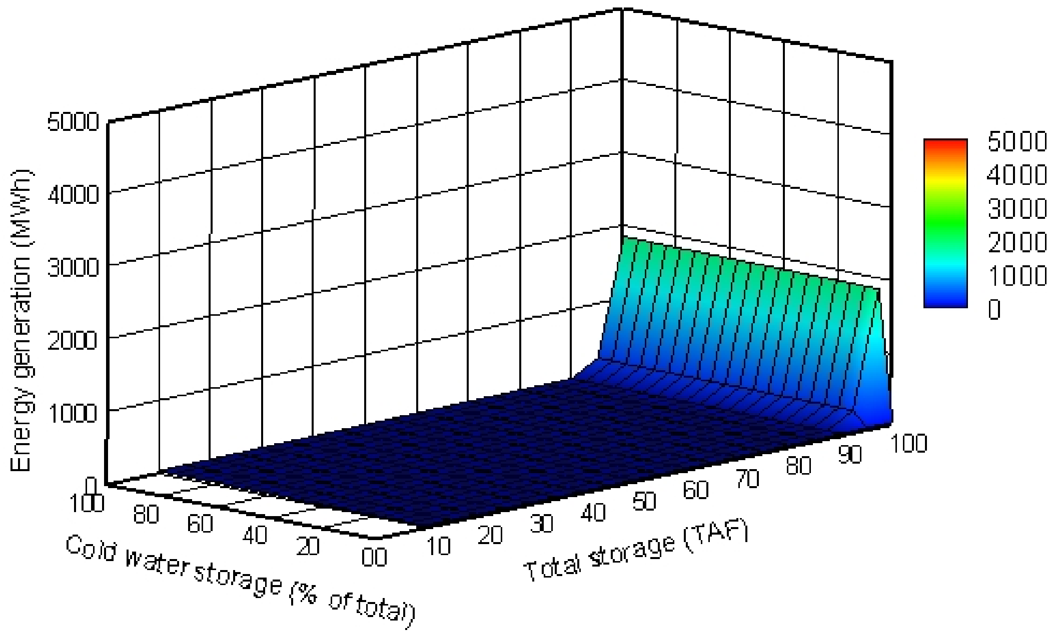

Figure 5.60: Expected energy production in the last week for minimum release of 10 cfs

5.6.4 Carryover storage

The crucial tradeoff faced by a reservoir operator involves consideration of the direct benefits of releasing water and the expected value of carryover storage, water that is kept in the reservoir for future periods. Unlike the results for total release or energy, no evident differences can be identified among the selected weeks. For this reason, only two of the selected weeks are shown, 1 and 14, respectively in Figs. 5.24 and 5.25. Results for the other 3 weeks selected for result presentation look undistinguishable from the surface of week 14. This is mainly due to a scale issue. All other variables kept constant, a decrease in 100 cfs in total release increases carryover storage by less than 1.4 TAF, practically not reflected for a scale as large as 100 TAF. Therefore, the drop in total release when the cold water storage is lowest cannot be easily appreciated.

However, close inspection of Fig. 5.25 permits identification of an increase in carryover storage when cold water storage is lowest. This is consistent with the decrease observed in total release when only the minimum flow can be released at the adequate temperature. A slight increase in carryover storage for week 14 consistent with the step-like reduction observed for total release can be identified from the source data of Fig. 5.25. Results differ between weeks 1 and 14 in two main aspects. First, carryover storage for any combination of state variables is higher in week 1. This reflects the higher inflows observed by the beginning of the season and also the low value of energy in the first week of summer. When the reservoir storage is at its minimum of 10 TAF at the beginning of week 1, carryover storage is above 20 TAF. Some concavity with respect to total storage can be identified for very high total storages. For initial storages of 95 TAF or above, the reservoir is full at the end of week 1.

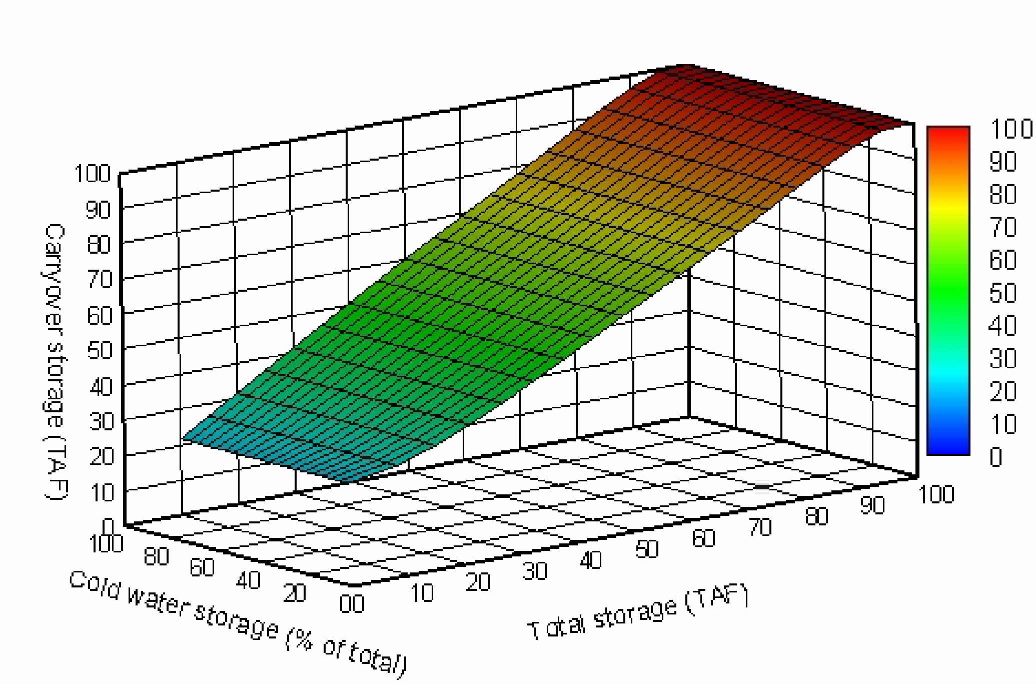

Figure 5.61: Expected carryover storage first week for minimum release of 10 cfs

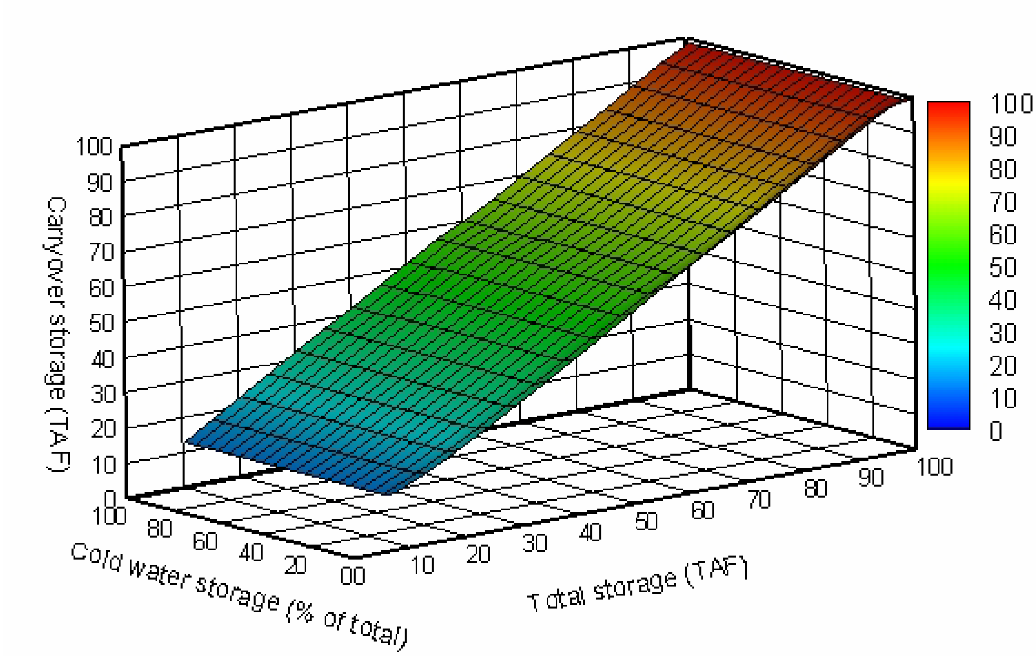

Figure 5.62: Expected carryover storage week 14 for minimum release of 10 cfs

Carryover storages for week 14 are generally lower than its counterpart for the first week of the season. If storage at the beginning of week 14 is the minimum 10 TAF, about 12 TAF are passed to week 15. The reservoir is never full at the beginning of week 15, not even when the maximum storage of 100 TAF at the beginning of week 14. This is due to the low inflows towards the end of the summer.

5.6.5 Hydropower revenues

Revenues drive hydropower reservoir operations. The revenues for each selected week are presented as surfaces in Figs. 5.26 through 5.30. Revenues include the effect of productive total release and energy price at a given week. As expected, revenues are highest for week 7, when energy price is highest, ranging between $80,000 and $220,000 per week depending on total storage. Week 14 follows closely, with revenues between $50,000 and $170,000. Much smaller revenues are generated during the other weeks shown. The effect of cold water storage as a limiting factor is observed for weeks 10, 14 and 17. The decreasing nature of average energy price with hydropower release (Fig. 5.14) is reflected in the revenues. The gradient of revenues in the direction of total storage is less pronounced than its energy counterpart. As energy production increases, the average price at which it is sold decreases, so the revenues increase less than proportionately to an increase in energy generation. This effect is particularly clear in weeks 1 and 7. The revenue surfaces (Figs. 5.26 and 5.27) look much flatter than the corresponding energy surfaces (Figs. 5.19 and 5.20).

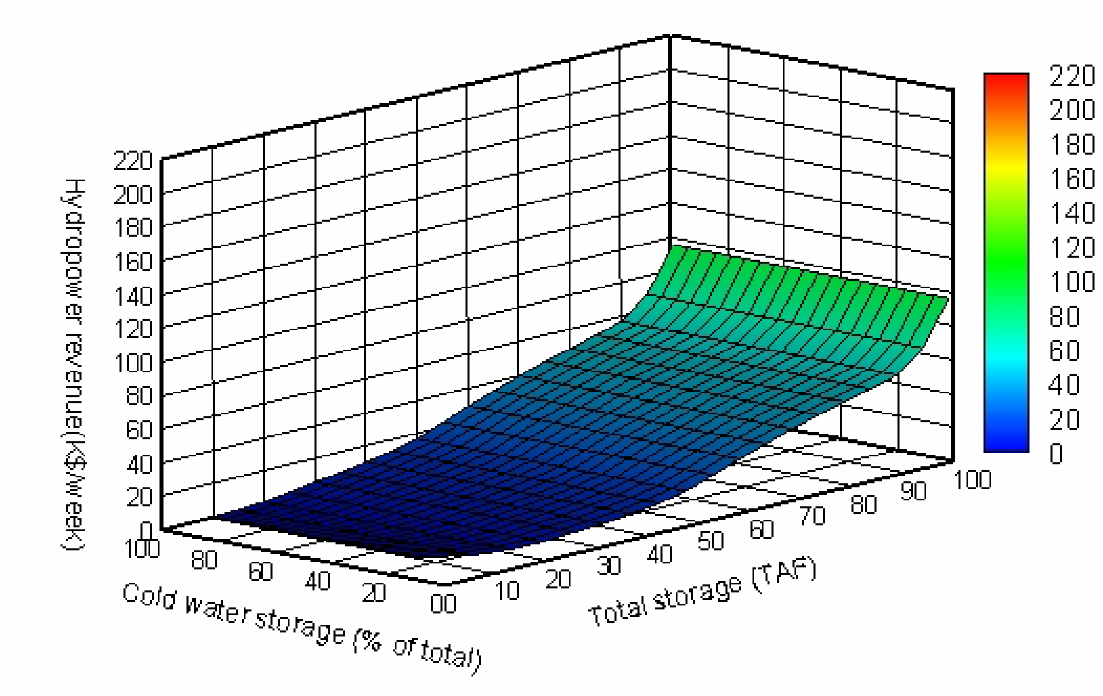

Figure 5.63: Expected hydropower revenues in first week for minimum release of 10 cfs

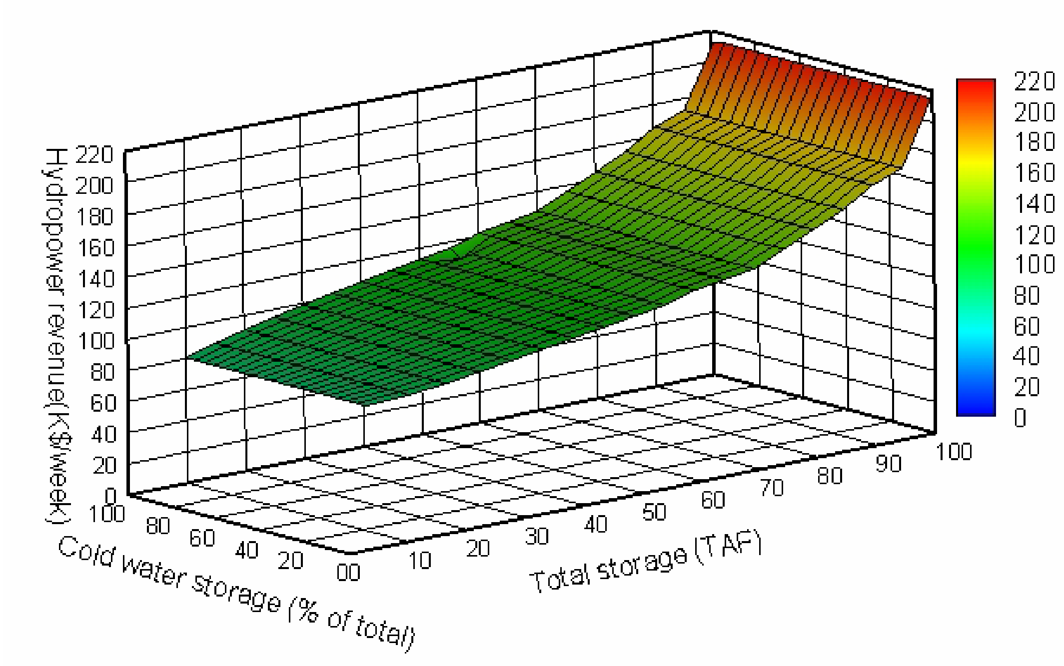

Figure 5.64: : Expected hydropower revenues in week 7 for minimum release of 10 cfs

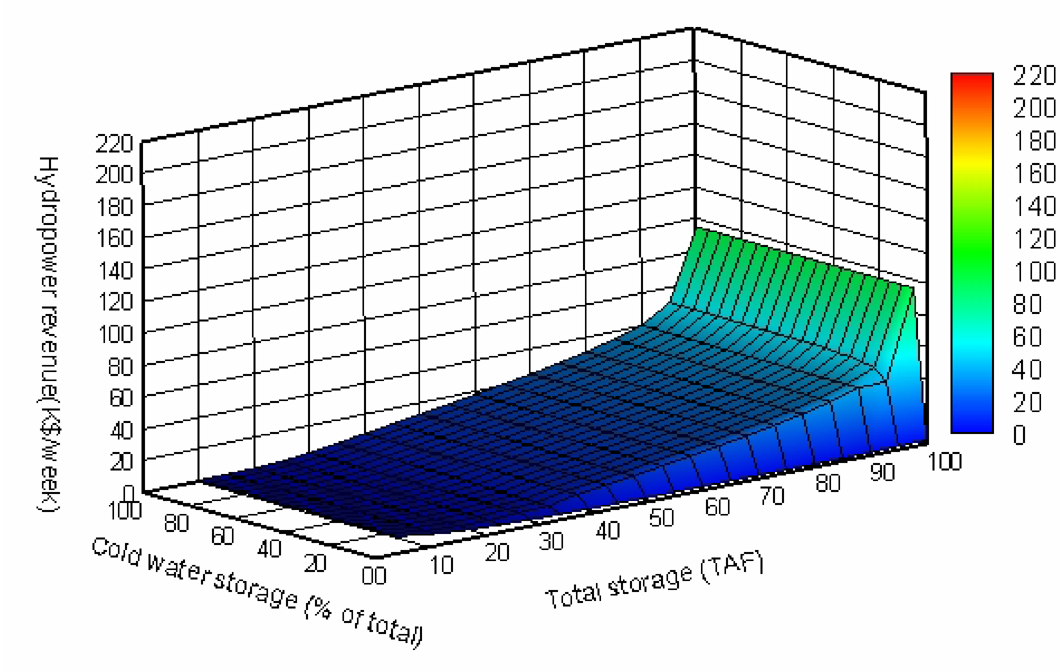

Figure 5.65: Expected hydropower revenues in week 10 for minimum release of 10 cfs

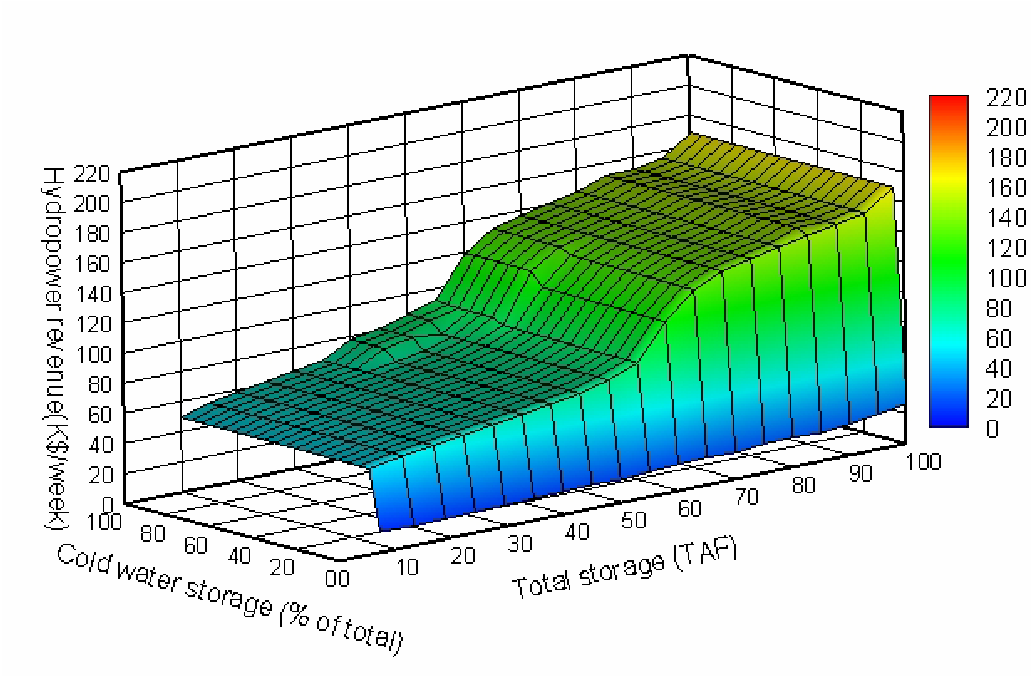

Figure 5.66: Expected hydropower revenues in week 14 for minimum release of 10 cfs

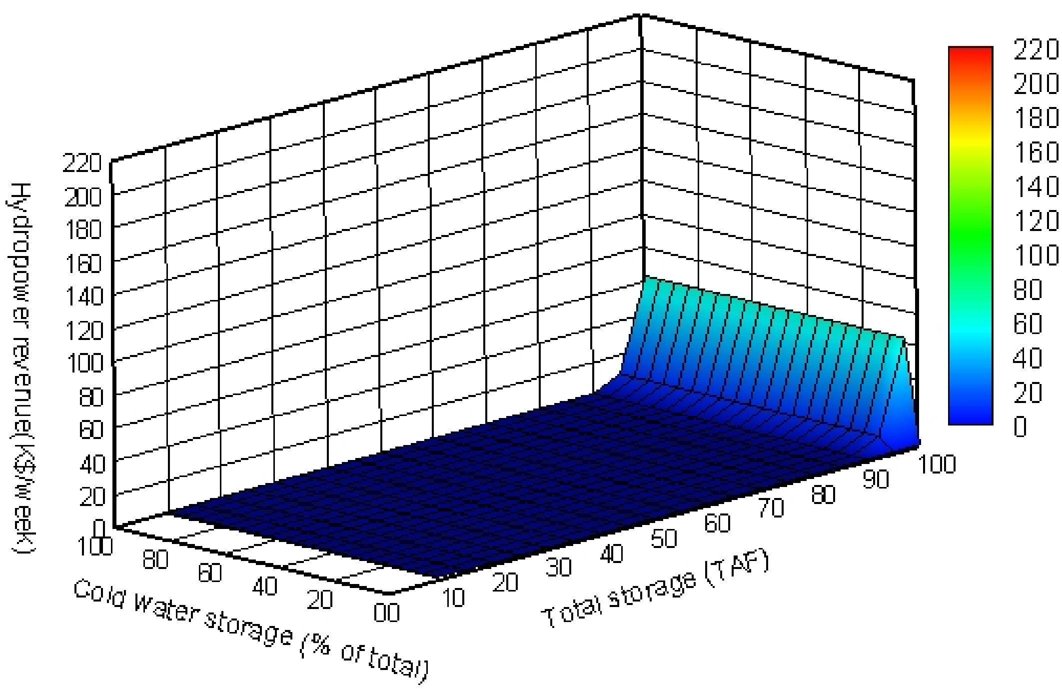

Figure 5.67: Expected hydropower revenues in the last week for minimum release of 10 cfs

5.6.6 Marginal cost of minimum release

The economic impact of an environmental constraint can be represented through the marginal change in the economic performance of the hydropower system due to a marginal change in the environmental requirement. In the case of minimum required release, its impact is two-fold. First, it enforces that at least the minimum amount is released even when it was not economically desirable. This is the typical marginal value associated with a minimum release constraint. Even when the hydropower release is greater than the minimum, the minimum flow has an effect of the revenues as indicated in Eq. 5.5, which capture the peaking nature of hourly operations. Since the minimum flow must be released at every hour during the week, that water cannot be allocated optimally to hours of high price. Energy from the minimum flow release is sold at the average price of all hours in the week. Energy above the minimum is produced by peaking operations and therefore captures a higher price.

The first effect, the marginal value of the minimum release constraint is a standard output of the optimization solver package GAMS. This value is zero whenever the release exceeds the minimum, indicating that no uneconomic releases are being forced. For weeks with high energy prices, like 7 and 14, the marginal cost on the constraint is generally zero, except for very dry inflow scenarios and when the cold water content is at its minimum. The marginal costs associated with the minimum flow level are presented for weeks 1, 10 and 17 in Figs. 5.31, 5.32 and 5.33, respectively. No evident effect can be attributed to the available content of cold water in the reservoir at the beginning of the week, except when very little cold water is available in week 10. When the cold water storage is just that needed for the minimum flow and the reservoir is not full, the cost of the minimum flow constraint reaches values between 10 $/cfs and 18 $/cfs. Fig. 5.32 shows that in week 10, for cold water content higher than the minimum feasible, the minimum required release has an economic effect only for total reservoir storages between 10 TAF and 30 TAF, with a cost of about 2 $/cfs.

In the first week of the season (Fig. 5.31) the marginal cost of minimum releases is zero for total storages above 50 TAF, regardless of the proportion of cold water available. Interestingly, the highest marginal cost of about 4 $/cfs occurs for a total storage of 30 TAF and not when storage is at its lower bound of 10 TAF, where the cost is about 1.5 $/cfs.

In the last week of the season, as a result of a relatively high energy price and low flow conditions, the marginal cost of the minimum flow averages about 4 $/cfs, twice as high as the average for week 10. Since energy prices for these two weeks are very similar, the higher cost of minimum release in the last week can be associated with its low expected inflow. When the reservoir is nearly full or full, the cost drops to about 1 $/cfs and practically zero, respectively.

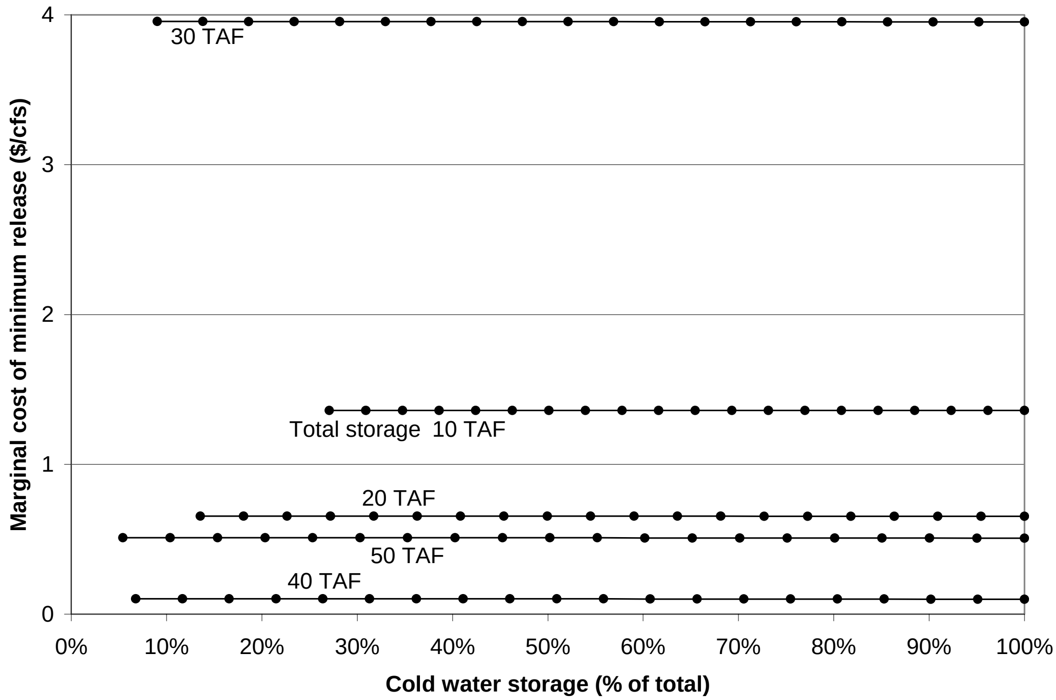

Figure 5.68: Average marginal cost of minimum release in the first week for selected total storage levels

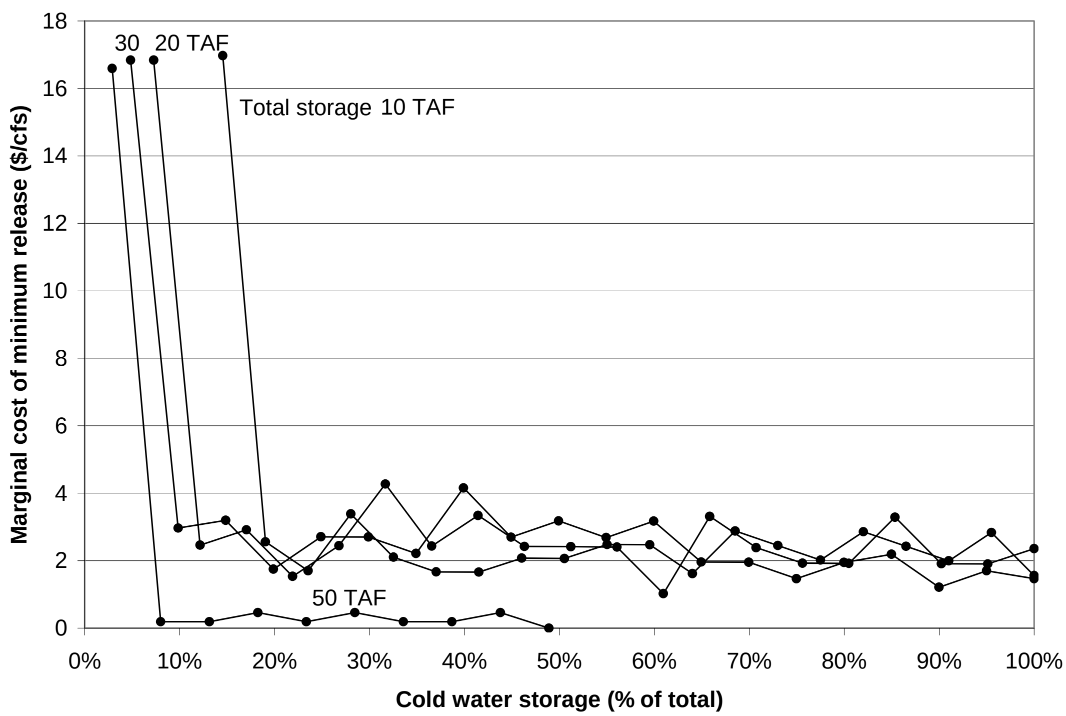

Figure 5.69: Marginal cost of minimum release in week 10 for selected total storage levels

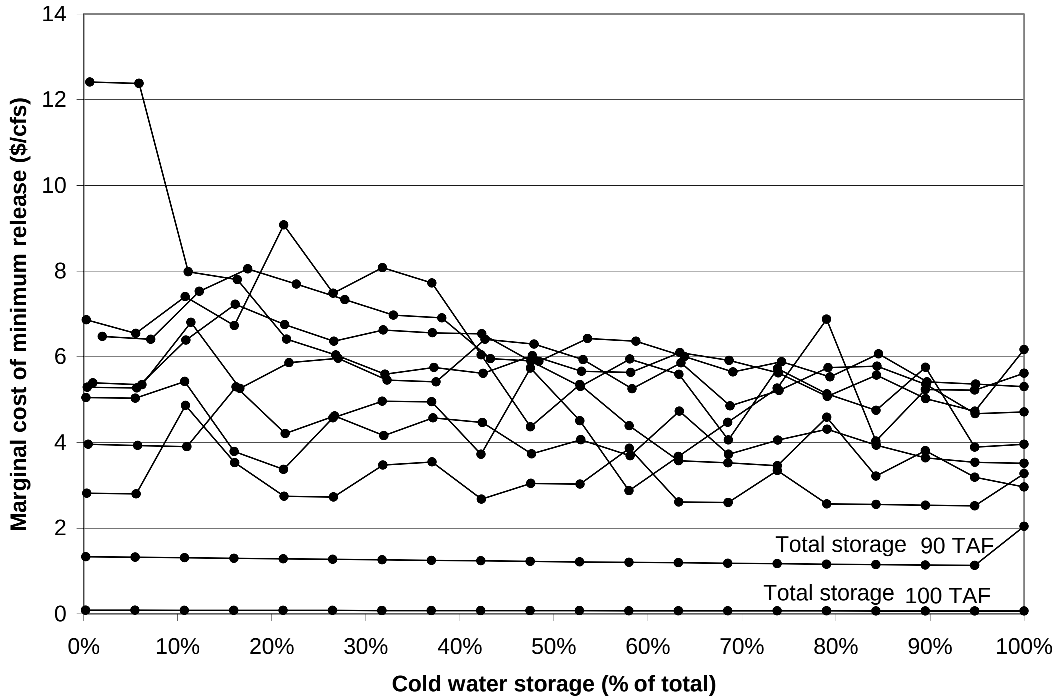

Figure 5.70: Marginal cost of minimum release in week 17 for selected total storage levels

5.6.7 Marginal cost of maximum temperature

Besides minimum releases, environmental impacts of hydropower operations are constrained by the maximum allowed release temperature. This restriction affects operations only after the upper layer becomes warmer than the temperature target. Its marginal cost is zero for weeks 1 through 7. The marginal costs for selected weeks are shown in Table 5.4. The normal range includes all values of total storage and cold water storage except when the cold water content is the minimum feasible to release the minimum flow at the maximum allowed temperature. In those instances, the marginal cost of the temperature constraint increases to reach the maximum values presented in the table. Other than that, no other effect of the cold water storage can be identified. As expected, the marginal cost is highest for week 14. Week 17 sees the lowest cost of the temperature requirement because energy price is low and therefore extra generation allowed by relaxing the temperature requirement does not have much value.

Table 5.7: Marginal cost of temperature requirement

Week	Normal range ($/°C)	Maximum ($/°C)
10	1 - 4	80
14	1 - 10	150
17	<2	20

5.7 Evaluation of scenario-dependant policies

Under the implicit stochastic approach adopted here, optimal policies are specific for each scenario. An interesting analysis is to evaluate the performance of those policies under a variety of different hydrologic scenarios, not only the one scenario used to derive such a policy.

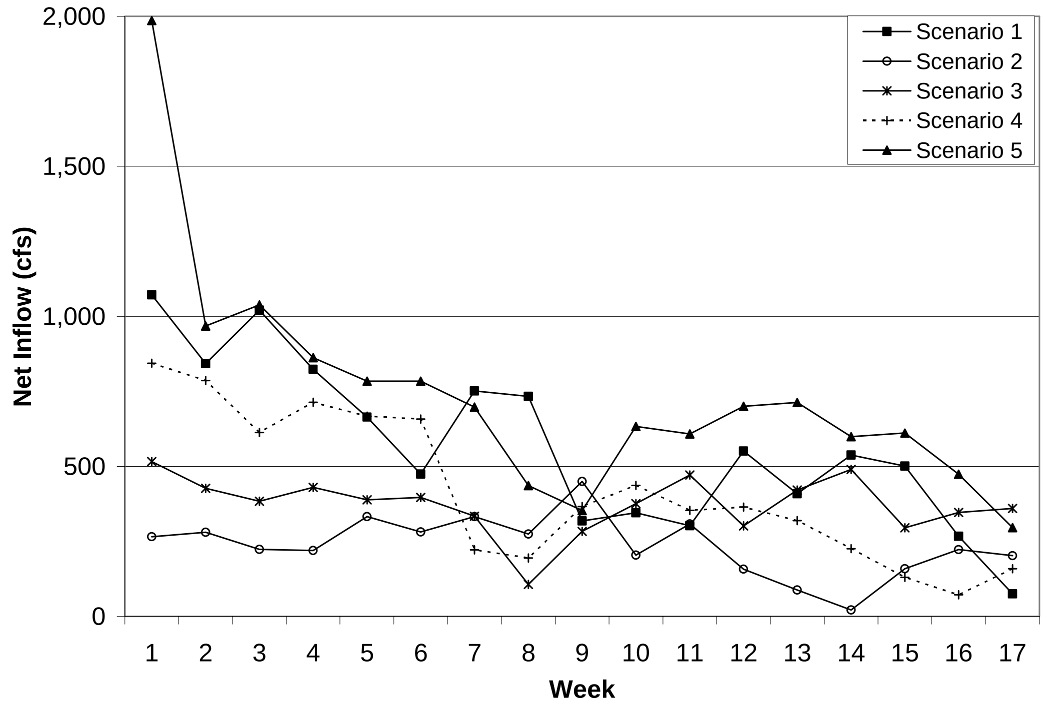

Figure 5.71: Selected inflow scenarios for policy evaluation

For illustrative purposes, consider the five inflow scenarios shown in Fig. 5.34. For each scenario, the optimal policy is obtained by re-optimization using the corresponding approximation of the value function obtained by dynamic programming. The performance of each policy, in terms of total revenues over the stratification season plus the value of ending storage, under all five scenarios is simulated by forward optimization. Results for an initial storage of 50 TAF (50% of storage capacity), with 25 TAF of cold water are shown in Fig. 5.35. The highest revenues for all policies are obtained under inflow scenarios 1 and 5, the two wettest scenarios. Scenario 2, the driest of all five scenarios have the lowest total benefit for each policy.

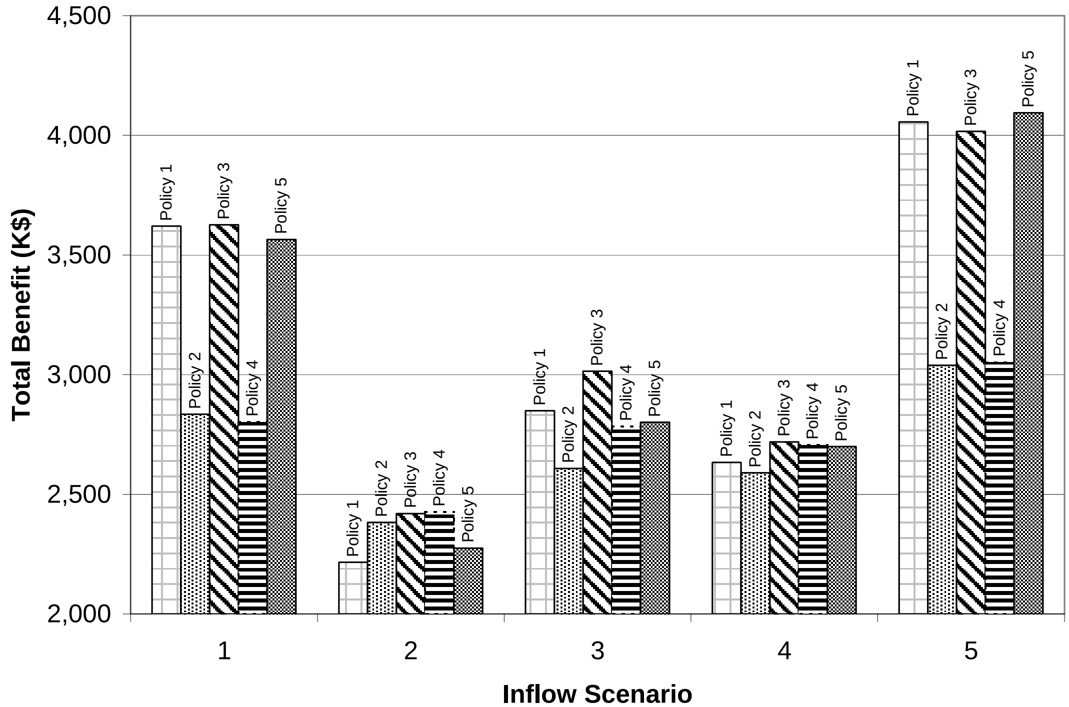

Figure 5.72: Total benefit of optimal policies under selected inflow scenarios

It is expected that, for each scenario, the associated policy outperformed all other policies. That result is clearly obtained for scenarios 1, 3 and 5. Interestingly, under the two driest scenarios (2 and 4), the corresponding policy is slightly outperformed by other policies. This difference can be attributed in principle to the error in the value function approximation. A very interesting result is that policy 3 seems to be optimal or near optimal under all five scenarios. In that sense, the policy obtained under scenario 3 is a robust policy for the five scenarios considered here. Policies 2 and 4 are only best (or nearly so) under the corresponding scenarios, but its performance is poor under other inflow scenarios.

5.8 Conclusions

This chapter develops and uses an optimization model for the optimal operation, with weekly release decisions, of a stratified reservoir with a temperature control device which allows selective choice of release from different reservoir levels. The thermal structure of the reservoir was simplified by considering two pools, a warm upper layer and a cold lower layer. The problem is formulated as hydropower revenue maximization subject to infrastructure and environmental constraints. The latter were represented by a minimum release required at all times and a maximum temperature for the combined release. To avoid a myopic behavior, the value of carryover storage at the end of the summer was estimated by application of value iteration in a dynamic programming model. An implicit stochastic dynamic program was implemented to optimize operation for an ensemble of 25 inflow series. It was considered that the state of the reservoir is properly represented by the total storage and the content of cold water. With dynamic programming, the multi-stage problem is solved one stage at a time. At each week of the season, given a total storage and its percentage of cold water, the model solves for optimal release from each of the two pools by trading off the immediate benefit of power generation and the future value of leaving water in storage, both warm and cold. A continuous approximation of the future value function was implemented using Chebyshev polynomials. With this approximation, the problem can be solved using standard nonlinear programming techniques.

In general, results show a much stronger effect of total storage on the economic performance and operational pattern of the reservoir. Total hydropower generation and revenues increase with total storage. Cold water storage affects operations and therefore revenues only when it is at its minimum feasible level (i.e. only the minimum flow can be released at the appropriate temperature) or when energy prices are very high. No effects are observed early in the season, when the upper layer is still cooler than the temperature target. This result can be related with the approximation scheme adopted for the future value function and the exclusion of part of the feasible values of cold water storage.

Examples of the results and analysis that can be performed with this model include the economic and environmental performance of the reservoir, as well as operational insights. Release temperature follows a very clear pattern. Until the upper layer becomes warmer than the maximum temperature allowed, the release temperature is the same as the temperature of the upper reservoir layer. No cold water is blended, but it is saved for warmer future periods. After the upper pool becomes warmer than the limit, cold water is released in amounts just to comply with the maximum temperature. Total reservoir releases follow the energy price pattern. More water is used for hydropower generation when energy is more valuable. When energy is relatively cheap, only the minimum required is released, unless the reservoir is nearly full. For all weeks, the total release tends to increase with the total storage. The effect of the percentage of cold water is evident when release temperature becomes a limiting factor for operations. When the cold water content is not sufficient to support the optimal total release at the adequate temperature, less than the desirable amount of water is passed through the turbines, reducing, the energy output and revenues.

The cost of the environmental restrictions is represented by the marginal value of the corresponding constraints. The marginal cost of the minimum flow increases as the season progresses because inflows become smaller. This cost is only realized when the economically optimal release would be smaller than the minimum required. The cost is zero for weeks with high energy value, because economically optimal releases are much higher than the minimum. The marginal cost of setting a maximum temperature for reservoir releases is only realized after the upper layer is warmer than the target temperature. This cost is highest when energy is most valuable and very little cold water is available.

Finally, the economic performance of five selected scenario-dependant policies under the corresponding five hydrologic scenarios was evaluated. The total benefit was calculated as the sum of hydropower revenues over the 17 weeks in the stratification period plus the value of storage at the end of the season. This analysis allows for identification of robust policies, those that perform well under a variety of scenarios.

5.9 Limitations and further research

The most relevant limitation of this chapter is related to the continuous approximation of the future value function for two dimensions in dynamic programming. The non-rectangular domain defined by the feasible values of warm water and cold water storage, the original state variables, led to representation of the state of the system by total storage and proportion of cold water. Since feasibility is defined by a minimum cold water volume and not a minimum proportion of cold water to total storage, the resulting domain is still not rectangular, although it can be approximated to a rectangle by excluding a part of the feasible space. More precisely, the entire range of feasible proportions of cold water is only explored when the total storage is lowest. For higher storage values, only proportions of cold water defined by the minimum total storage are explored.

On the other hand, the future value function was less smooth than expected with respect to the cold water content. It decreases abruptly when the cold water storage becomes very small. This abrupt behavior cannot be properly represented by low degree Chebyshev polynomials. In fact, the problem of continuous approximation of a concave, increasing (but not monotonically so), non-regular function remains a very difficult problem. Unsuccessful attempts were made as part of this work to extent the work by Schumaker (1983) on one-dimensional quadratic approximation for shape-preserving. However, even if a shape-preserving approximation is implemented, the problem of having a non-rectangular domain will persist.

Therefore, further research is needed to improve the value function approximation for the intra-season model to allow more conclusive results regarding the effect of cold water on the economic performance and operational aspects of the problem. Specifically, a method for bivariate, shape-preserving function approximation over a non-rectangular domain needs to be developed. A starting point would be the extension of the shape-preserving algorithm for bivariate function approximation over a rectangular domain developed by Costantini and Fontanella (1990) and later applied by Wang and Judd (2000).

Another direction for further research that is already being explored is the implementation of an explicitly stochastic version of the dynamic programming model.

5.10 References

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CHAPTER 6

CONCLUSIONS AND FUTURE RESEARCH

6.1 Conclusions

This dissertation employs optimization models to explore some engineering solutions to alleviate the conflict between hydropower operations and downstream ecosystem maintenance. The present work includes operations with release decisions made at hourly and weekly intervals. Hourly peaking operations during a typical summer day were modeled for a reservoir-afterbay hydropower complex, under regulatory constraints defining minimum instream flows (MIFs) and maximum ramping rates (MRRs). Since revenues obtained at any longer time scale are the result of hourly operations, a method is proposed to incorporate hourly price and operational information on the revenues obtained at daily, weekly, or monthly decisions level. The method explicitly includes the effect of minimum stream flows on the economic benefits obtained by hydropower generation. Optimal weekly release decisions for a stratified reservoir with selective withdrawal were explored using a dynamic programming approach. Operations were constrained by minimum releases and maximum release temperature.

Engineering solutions, when optimally operated, are useful to efficiently attain ecosystem-related targets. In the case of hourly operations, a small afterbay can mitigate the economic impact of release constraints by dampening the connection between hydropower generation flows and releases to the stream. With an afterbay, the cost imposed by stringent MIF or MRR requirements decreases considerably. As MIF and/or MRR requirements become more stringent, operations depart from the unconstrained peaking. An afterbay buffers this effect through an operation pattern characterized by a morning drawdown and some refill cycles during peak hours. With an afterbay, several alternative instream flow patterns are optimal. Expert judgment can be used to choose one over the others.

The proposed method for estimating revenues at larger time scales using hourly operational information performs very well when compared to the revenue obtained by hourly optimization, outperforming the traditional two-block price structure approach.

The model for temperature management shows a much stronger effect of total storage on the economic performance and operational pattern of the reservoir. Total hydropower generation and revenues increase with total storage. Cold water storage affects operations and therefore revenues only when it is at its minimum feasible level (i.e. only the minimum flow can be released at the appropriate temperature) or when energy prices are very high. No effects are observed early in the season, when the upper layer is still cooler than the temperature target. This result can be related with the approximation scheme adopted for the future value function and the exclusion of part of the feasible values of cold water storage.

6.2 Future research

Further research efforts can take several directions. The incorporation of more explicit ecosystem goals than minimum flow, ramping rates, and maximum release temperatures is limited by the lack of quantitative relationships between operational patterns and its effect on desirable ecosystem attributes. Advances in this direction are needed. Other than that, the proposed method to link hourly operations with revenues on larger time frameworks can be extended to include uncertainty of the price duration curve, which was assumed to be perfectly known here. The model for temperature management would be considerably improved by a better approximation of the value function. Specifically, a method for bivariate, shape-preserving function approximation over a non-rectangular domain needs to be developed.