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Modeling California's high-elevation hydropower systems in energy units

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[1] This paper presents a novel approach for modeling high-elevation hydropower systems. Conservation of energy and energy flows (rather than water volume or mass flows) is used as the basis for modeling more than 135 high-elevation high-head hydropower sites throughout California. The unusual energy basis for reservoir modeling allows for development of hydropower operations models for a large number of plants to estimate large-scale system behavior without the expense and time needed to develop traditional streamflow and reservoir volume-based models in absence of storage and release capacity, penstock head, and efficiency information. Potential applications of the developed Energy-Based Hydropower Optimization Model (EBHOM) include examination of the effects of climate change and energy prices on system-wide generation and hydropower revenues. An extensive comparison of the EBHOM with a traditional hydropower optimization model used in California produced similar results and indicated good reliability of EBHOM's predictions.

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1. Introduction

[2] Hydroelectric power's low cost, near-zero pollution emissions, and ability to quickly respond to peak loads make it a valuable renewable energy source. In the mid-1990s, hydropower was about 19% of world's total electricity generation [*Lehner et al.*, 2005]. Worldwide hydroelectric generation from 1990 to 2020 could grow between 2.3 and 3.6% per year [*European Commission*, 2000; *Lehner et al.*, 2005].

[3] Depending on hydrologic conditions, hydropower provides 5–10% of the electricity used in the United States [*National Energy Education Development Project*, 2007] and almost 75% of the nation's electricity from all renewable sources [*Energy Information Administration*, 2005, Table 18; *Wilbanks et al.*, 2007]. No major electricity generation source is cheaper; while it costs almost 4 cents and 2 cents for 1 kWh of electricity from coal and nuclear plants, respectively, hydropower generation typically costs only about 1 cent per kWh [*National Energy Education Development Project*, 2007].

[4] About 75,000 MW of hydropower generation capacity exist in the United States, equivalent capacity to 70 large nuclear power plants [*National Energy Education Development Project*, 2007]. More than half of U.S. hydroelectric capacity is in the western states of Washington, California and Oregon, with approximately 27% in Washington (Energy Information Administration, Energy kid's page, 6 November 2007, available at http://www.eia.doe.gov/kids/energyfacts/sources/renewable/water.html). Hydropower facilities in the United States are diverse. Facilities range from multipurpose dams with large reservoirs to small run-of-river dams with little or no active water storage [*National Energy Education Development Project*, 2007]. Plant elevations also vary. In California multipurpose dams are usually at lower elevations, with higher elevation plants operating primarily for hydropower.

[5] California relies on hydropower for 9–30% of electricity used, depending on hydrologic conditions [*Aspen Environmental Group and M. Cubed*, 2005]. California's high-elevation hydropower system is composed of more than 150 power plants, above 305 m (1,000 feet) elevation. This system, which mostly relies on snowmelt, supplies roughly 74% of California's in-state hydropower, although only about 30% of in-state usable reservoir capacity is at high elevations, above 305 m [*Aspen Environmental Group and M. Cubed*, 2005]. The high-elevation reservoirs are predominantly single-purpose reservoirs for generating hydropower [*Aspen Environmental Group and M. Cubed*, 2005; *Vicuna et al.*, 2008] with some secondary benefits such as flood control. These reservoirs are mostly privately owned, regulated by U.S. Federal Energy Regulatory Commission (FERC), and operated for hydropower revenues. The high-elevation hydropower plants are generally located below small (within-year storage) reservoirs with high turbine heads compared with much larger multipurpose reservoirs with lower head downstream (lower elevations).

[6] California's Mediterranean climate has one wet season and a long dry season; 75% of annual precipitation occurs from November through March. These single-purpose reservoirs (except for a few such as Lake Almanor) are emptied by the end of the hydrologic year (September) to capture fall and winter precipitation and spring snowmelt. Since electricity prices are high in summer, it is reasonable to generate and sell hydropower instead of risking energy spill in the wet

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season when energy prices are lower. Therefore, only one major drawdown-refill cycle per year is typical for hydropower and water supply operations in California.

[7] Hydropower generation varies greatly between years with varying inflows, as well as competing water uses, such as flood control, water supply, recreation, and in-stream flow requirements (for water rights, navigation, and protection of fish and wildlife) [*National Energy Education Development Project*, 2007]. Given hydropower's economic value and its role in complex water systems, it is reasonable to seek optimal operation of hydropower generation and adaptation to changing conditions. Optimization modeling is common for studying the performance of hydropower systems under different conditions and for guiding reservoir operations. Conventional simulation and optimization methods used for hydropower systems [*Grygier and Stedinger*, 1985; *Arnold et al.*, 1994; *Jacobs et al.*, 1995; *Vicuna et al.*, 2008] are quite useful but their application to extensive hydropower systems is intensive, costly, and often proprietary. For instance, there are 2,388 hydropower plants in the United States, 411 plants are in California [*Hall and Reeves*, 2006]. Studying climate change effects on hydropower generation in the United States or even in California through conventional detailed modeling of each system requires large investments of time and money, especially when basic information such as stream flows, turbine capacities, storage operating capacities, and energy storage capacity are not readily available for each plant. Given the proprietary nature of most existing hydropower models and data, there is value for a less detailed method of modeling extensive hydropower systems lacking detailed information. This paper introduces a new method for studying optimal operation of high-elevation systems, which operate predominantly for hydropower, with high head and negligible over-year storage, in absence of detailed information.

[8] Energy-based modeling of single-purpose hydropower systems is presented, along with application to 137 hydropower plants throughout California. We begin with the general model formulation, followed by novel methods for estimating the energy storage capacity of hydropower units and representing hourly varying prices in reservoir models at larger time scales. A small change in the formulation is introduced for cyclic seasonal operations. Comparison of model generation estimates is made with the historical generation in an average hydrologic year at a particular facility in California. Discussion of the general estimation of parameters for 156 hydropower plants in California is made. Then the model is applied to estimate optimal monthly energy generation at 137 hydropower plants in California for a 14 year period. The paper concludes with a discussion of potential applications, limitations, and conclusions. The primary advantage of this approach is to develop policy and operational insights for large numbers of hydropower plants where traditional reservoir model development and estimation would be prohibitively costly and time consuming.

2. Energy-Based Hydropower Optimization Model (EBHOM)

[9] Unlike conventional models, where calculations are in volumetric units, the Energy-Based Hydropower Optimization Model (EBHOM), introduced here, is a monthly step model which does all storage, release, and flow calculations in energy units. EBHOM is developed to investigate the performance of the system under different conditions and can contribute to studies in which active storage capacity data and penstock head information are unavailable. In such studies, energy storage capacity for each unit can be calculated on the basis of differences in seasonal water inflow distribution and energy generation data. EBHOM can then be used to explore the optimal operation of the system for different scenarios.

[10] Most high-elevation hydropower plants operate for net revenue maximization [*Jacobs et al.*, 1995]. Lower-elevation plants tend to operate for a greater variety of purposes. Since hydropower operating costs are essentially fixed (at monthly scale), an operational surrogate for net revenue maximization is revenue maximization. EBHOM's simple general mathematical formulation (in energy units) is

$$Maximize\ Z = \sum_{i=1}^{12} P_i \times G_i \tag{1}$$

subject to

$$S_1 = 0 (\text{initial condition}) \tag{2}$$

$$S_i \leq Scap\, (\text{energy storage capacity}),\ \forall i \tag{3}$$

$$S_i = e_{i-1} + S_{i-1} - R_{i-1} (\text{conservation of energy}),\ \forall i \tag{4}$$

$$G_i \leq R_i,\ \forall i \tag{5}$$

$$G_i \leq Gcap\, (\text{generation capacity}),\ \forall i \tag{6}$$

$$G_i, S_i, R_i \geq 0\, (\text{nonnegativity}),\ \forall i (i = 1, 2, 3, \ldots, 12) \tag{7}$$

where Z = revenue; G_i = hydropower generation in month i (MWh/month); P_i = price of electricity in month i ($/MWh); S_i = energy storage at the beginning of month i (MWh); $Scap$ = energy storage capacity (MWh); e_i = energy runoff in month i (MWh); R_i = energy release in month i (MWh/month) (decision variable); $Gcap$ = generation capacity (MWh/month); and i = 1 corresponds to the first month of the refill cycle with energy storage at the beginning of this month set equal to zero (equation (2)).

[11] This formulation is valid when the reservoir is used only for hydropower generation, and primarily for seasonal (as opposed to over-year) storage. The formulation also requires a "high-head" condition where storage does not significantly affect hydropower head.

3. Estimating Seasonal Energy Storage Capacity

[12] Normal estimation of a reservoir's energy storage capacity involves integrating the potential energy content over all reservoir elevations, presuming detailed knowledge of penstocks, reservoir geometries, and bank storage. Obtaining storage capacity data and penstock head information for

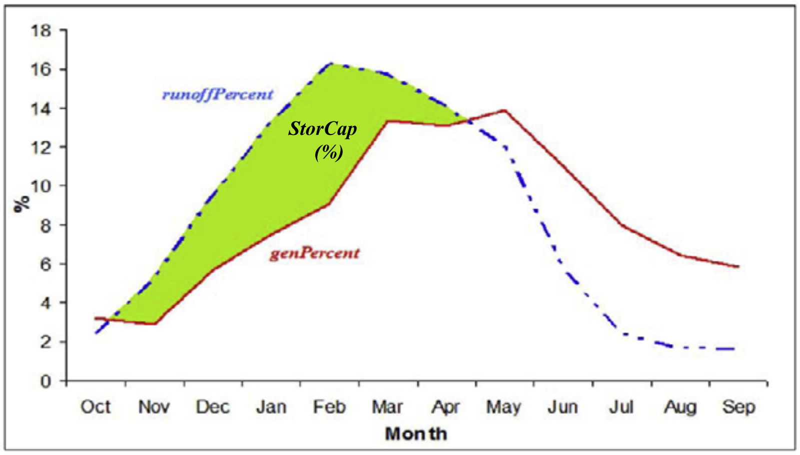

Figure 1. Calculation of operational storage capacity belonging to White Rock hydropower plant based on NSM. The shaded area between the two curves represents reservoir storage capacity in percentage of annual inflows.

many individual reservoirs is a big obstacle in large-scale hydropower systems modeling, especially if they belong to private owners with proprietary interests in information. Even if volumetric storage capacities were available, conventional estimation of energy storage capacities (that portion of the capacity storing water for electricity generation) would have been tedious and probably unreliable. To estimate the energy storage capacity of each power plant, it is assumed that the existing storage and release capacities of a high-elevation hydropower reservoir are sufficient to operationally accommodate the runoff in an average water year without water spilling from the reservoir.

[13] The proposed no-spill method (NSM) estimates seasonal energy storage capacity under the following conditions.

[14] 1. The reservoir does not spill energy in the average year, and all releases are made through the turbines. Energy spill results when runoff energy is lost from the system because it can be neither stored nor sent through the turbines because of limited storage and turbine capacities. Energy spill is the energy value of the available runoff which cannot contribute to energy production. For California, this lack of spill in an average year was confirmed in conversations with the private hydropower operators of most high-elevation plants in California. This condition sets a lower bound for storage capacity estimation. Actual reservoir capacity will exceed this lower bound if the reservoir does not fill in an average year. However, for calculation purposes it is assumed that the reservoir fills in an average year, making the approach pessimistic.

[15] 2. The power plant is a high-head facility where the effect of reservoir storage on turbine head is small. Generally, turbine head in high-elevation hydropower facilities is mostly from penstock drops, rather than additional elevation within the reservoir. This allows a linear relationship between water and energy stored in the reservoir, and seems common for many proprietary models for this system.

[16] 3. The seasonal distribution of inflow is known. Average seasonal flow distributions from nearby gages are used here to reflect seasonal runoff and snowmelt conditions.

[17] 4. There is only one major drawdown-refill cycle per year. Hydropower reservoirs typically fill once each year in California.

[18] High-elevation hydropower facilities usually have a within-year storage pool and mostly have watersheds above 305 m (1,000 feet). In California, many of these systems rely on snowpack to increase seasonal storage.

[19] The NSM estimates seasonal storage capacity in energy units by finding the area between the monthly runoff and monthly generation curves when both are expressed as monthly percentages of the annual average quantity. In month i, the runoff percentage ($runoffPercent_i$) and generation percentage ($genPercent_i$) can be calculated by dividing the average runoff in month i ($average\ runoff_i$) and the average generation in month i ($average\ generation_i$) by the average annual runoff (*average annual runoff*) and the average annual generation (*average annual generation*), respectively:

$$runoffPercent_i = \frac{average\ runoff_i}{average\ annual\ runoff} \tag{8}$$

$$genPercent(i) = \frac{average\ generation(i)}{average\ annual\ generation} \tag{9}$$

In percentage terms, the sum of differences between the two curves for a year (12 months) should be zero:

$$\sum_{i=1}^{12} (runoffPercent_i - genPercent_i) = 0 \tag{10}$$

In the 12 month period there are months i when the runoff percentage exceeds the generation percentage (when some runoff is stored in the reservoir) and months j when the generation percentage exceeds the runoff percentage (when some hydropower is generated by releasing stored water).

$$\sum_i (runoffPercent_i - genPercent_i) - \sum_j \left(genPercent_j - runoffPercent_j\right) = 0 \tag{11}$$

So, with only one refill-drawdown cycle per year, little over-year storage, and the reservoir on the verge of spilling at its fullest, the seasonal storage capacity (*StorCapPercent*) as a percent of total inflow is (Figure 1)

$$StorCapPercent = \sum_i (runPercent_i - genPercent_i) \tag{12}$$

or

$$StorCapPercent = \sum_j \left(genPercent_j - runoffPercent_j\right) \tag{13}$$

Multiplying the storage capacity percentage (*StorCapPercent*) by the average annual generation gives the active (operational) energy storage capacity (*Scap*):

$$Scap = StorCapPercent \times average\ annual\ generation \tag{14}$$

Multiplying the storage capacity percentage by the average annual runoff gives the volumetric active (operational) water storage capacity (*WScap*) directly used for hydropower generation:

$$WScap = StorCapPercent \times average\ annual\ runoff \tag{15}$$

This method produces a lower-bound estimate of energy storage capacity, as many reservoirs will not spill or fill in wetter than average years. The NSM also assumes reservoirs have negligible over-year storage, which is true for high-elevation hydropower reservoirs in California with a few exceptions (such as Lake Almanor).

[20] Figure 1 shows how the active storage capacity for the White Rock hydropower plant, with generation capacity of 165 GWh per month and average annual generation of 537 GWh in California was estimated using NSM. Monthly generation data were available for the years 1985 to 1998. Monthly runoff (inflow) data were obtained from U.S. Geological Survey (USGS) gauges. The mean monthly and mean annual runoffs were estimated for the study period. Mean monthly runoff and mean monthly generation were then normalized into percent of mean annual runoff (equation (8)) and mean annual generation (equation (9)), respectively, as shown in Figure 1. On the basis of equation (12) or equation (13), the shaded area between the two curves (22.5%) represents the storage capacity as a percentage of total generation or flow (*StorCapPercent*). Active storage capacity of this reservoir (the portion of actual energy storage capacity used for storing water for hydropower) was found to be 121 GWh (equation (14)).

[21] At a monthly time scale, several stair-stepped power houses (in series) might benefit from water stored in one upstream reservoir. When one power plant draws water from several upstream reservoirs (in parallel or series) the energy storage calculated for the power plant will reflect the total effective energy storage upstream of the plant. For instance for 2 reservoirs in series, the effective storage capacity belonging to the power station located below the second (lower) reservoir is determined on the basis of the difference between the undisturbed (natural) runoff to the first reservoir and the energy outflow from the second power plant. In that case, the calculated storage capacity is the effective storage capacity of the lower reservoir plus the portion effective storage capacity of the upper reservoir used for regulating inflow to the lower reservoir. Indeed, in this case the difference between the runoff and generation curves could be smaller without an upstream reservoir. However, with an upstream reservoir, energy is stored in the upper reservoir for some period, so the total effective energy storage capacity is higher than the energy storage capacity of the lower reservoir. This can become more complicated, as inflows for downstream power plants might be dominated by releases from upstream plants, not the assumed monthly inflow distribution for the power plant. Ultimately, this is a limitation of such coarse less detailed modeling. Incorporating such effects would require much greater modeling effort, which we needed to avoid here.

4. Energy Price Representation

[22] If fixed monthly energy prices are used in equation (1), EBHOM is linear as done in studies by *Vicuna et al.* [2008] and *Madani and Lund* [2007]. However, if fixed monthly energy prices are used, while maximizing revenue, the model suggests no generation in months with low prices to allow more generation in months with higher average prices, within storage capacity limits [*Madani and Lund*, 2007]. In real electricity markets, prices fluctuate hourly and marginal revenues of generation decrease with increased hours of generation. Linear EBHOM (monthly model) does not capture the varying nature of energy prices and the considerable effects of on-peak and off-peak pricing on the revenues. Considering on-peak and off-peak monthly prices in the linear model [*Vicuna et al.*, 2008] captures some effects of nonconstant energy prices. It is possible to explicitly capture the varying nature of energy prices if a linear EBHOM is formulated on an hourly basis. However, requires 730 times more decision variables (one month is 730 h on average). To decrease calculation time and effort, EBHOM can be formulated on a monthly basis as a concave nonlinear problem to represent on-peak and off-peak price variability, with a revised objective function (equation (1)) as follows:

$$Maximize\ Z = \sum_{i=1}^{12} P_i(h_i) \times G_i \tag{16}$$

where average monthly energy price $P(h_i)$ is a function of total hours of generation in month i. The variation in price with generation is not a result of price effects from an individual power plant's generation. Instead, this price variation represents the hourly variability in energy prices of the overall energy market responding mostly to continuous on-peak and off-peak variability in energy demands. Price for an individual plant's operation varies with the number of hours it operates. Since these plants are run to maximize power revenues, they are assumed to be operated in hours when the energy market offers higher prices.

[23] If a plant operates for hydropower, then the frequency distribution of hourly hydropower prices (Figure 2) can be integrated into an average revenue function of turbine release as a percent of monthly turbine capacity (Figure 3). If operating only for hydropower, a utility will release first at high-valued times and only release at lower-valued times

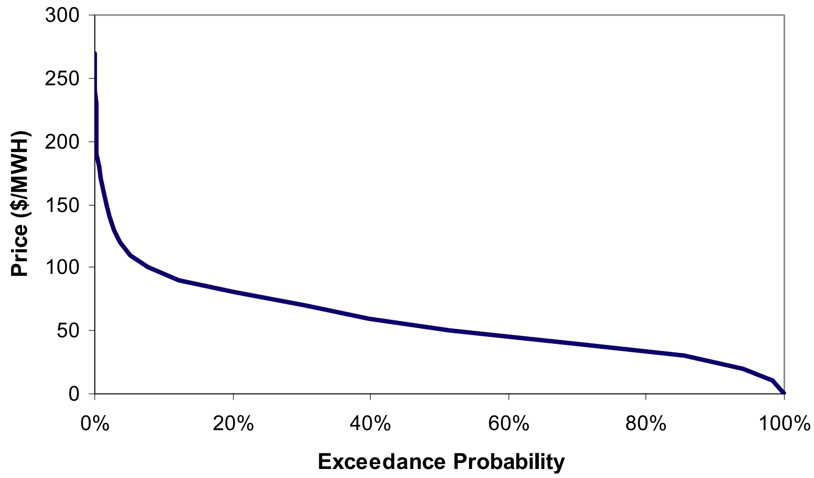

Figure 2. Frequency of California's hourly hydroelectricity price in October 2005 (Oasis Web site, http://oasis.caiso.com/).

as water becomes more abundant. The resulting benefit function allows approximate representation of hourly pricing within a monthly model. Hourly price frequencies from 2005 are used to develop revenue functions for each month (2005 prices were used only because of unavailability of price data for earlier years). Figure 2 shows the frequency of real-time market hourly energy prices in October 2005 in California, spanning on-peak and off-peak prices. For optimal hydropower operations, average energy price declines as hours of generation increase, so small releases are targeted for the maximum energy price and lowest average price occurs when release equals generation capacity. Since monthly generation increases by increasing the hours of turbine run, it is assumed that revenue from each plant is a function of the proportion of used monthly generation capacity:

$$z_i(h_i) = z_i(g_i) \tag{17}$$

where g_i is the proportion of monthly generation capacity used:

$$g_i = \frac{G_i}{Gcap} \tag{18}$$

Integration over the price curve in a given month (Figure 2) gives that month's revenue (z_i) as follows:

$$z_i(g_i) = Gcap. \int_0^{g_i} P_i(g_i)dg_i \tag{19}$$

Using equation (19), concave revenue curves for each month (October in this example) can be derived, as shown in Figure 3. In Figure 3, the horizontal axis shows g_i (October), and the vertical axis shows the corresponding average revenue per unit of plant generation capacity ($\frac{z_i(g_i)}{Gcap}$). From Figure 3, if the power plant generates at its full capacity in October, revenue at that power plant is 48 \$/MWh times its generation capacity. Revenue curves for any given fixed-head Californian hydropower plant in each month can be derived by multiplying both axes of Figure 3 by generation capacity of that power plant. Such curves can then be piecewise linearized or included nonlinearly, and summed over the months for the objective function of EBHOM (equation (16) as follows):

$$Maximize\ Z = \sum_{i=1}^{12} z_i(g_i) \tag{20}$$

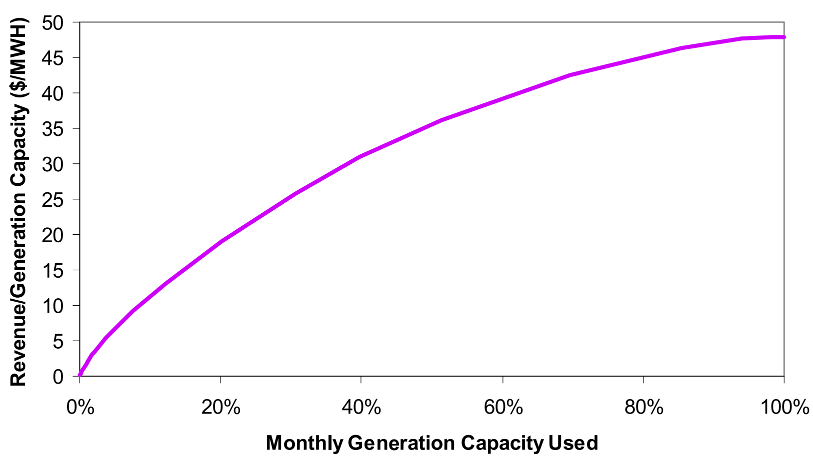

Figure 3. Revenue generation correlation in October 2005 (Oasis Web site, http://oasis.caiso.com/).

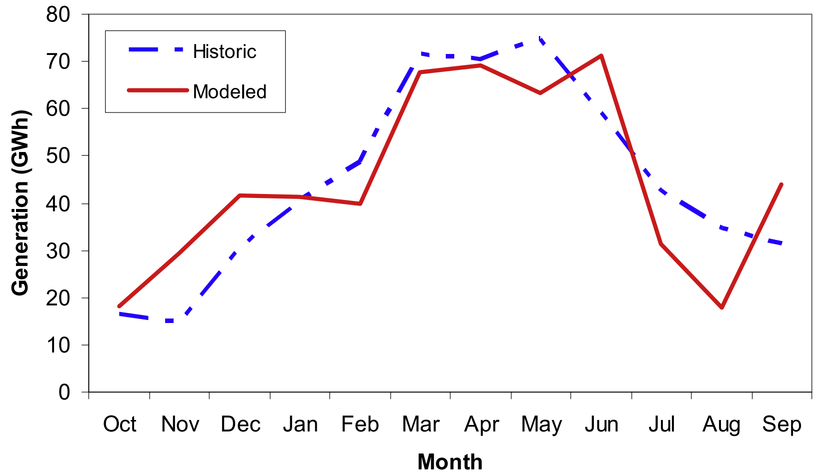

Figure 4. Comparison of average historical monthly electricity generation and optimal monthly electricity generation (found by EBHOM) at White Rock Hydropower Plant in California.

This formulation reflects continuous on-peak on off-peak energy grid prices. These energy market prices occur for the same hours of the day, across all plants. The price does not decrease because of the quantity of energy generated, but because of the hours of the day generated.

5. Reformulation for Cyclical Operations

[24] The EBHOM, as defined earlier, can be sensitive to the initial storage condition (equation (2)). Each reservoir has a specific refill and drawdown cycle. To find the best initial condition (refill month) for a single reservoir, the EBHOM could be run 12 times for the 12 different possible refill months, saving the decision values from the best performing refill month.

[25] Although simple and comprehensible, running the model 12 times for each reservoir requires excessive computation time for large systems. To decrease the calculation time the formulation is revised by replacing the first two constraints (equations (2) and (3)) with the following four constraints:

$$S_1 = big\,(\text{initial condition}) \tag{21}$$

$$S_{\min} \leq S_i,\ \forall i \tag{22}$$

$$S_i \leq S_{\max},\ \forall i \tag{23}$$

$$S_{\max} - S_{\min} \leq Scap\,(\text{storage capacity constraint}) \tag{24}$$

where big = an arbitrary large number exceeding *Scap*; $S_{\min}$ = minimum energy storage during the year (12 months period) (a decision variable); and $S_{\max}$ = maximum energy storage during the year (a decision variable).

[26] This formulation sets initial storage at a large nominal level (*big*). Storage changes are then made conventionally around this nominal level, with storage constrained to return to this initial level. The storage capacity constraint is enforced by defining the minimum and maximum storages from all months (equations (22) and (23)), and then constraining the difference (equation (24)), which is the amplitude of the annual drawdown-refill cycle. This limits real storage within the real storage capacity. Since the nominal initial storage exceeds the reservoir's capacity, nominal storage cannot become negative.

6. Comparison for White Rock Power Plant

[27] Figure 4 compares the average historical (recorded) hydropower generation (period 1985–1998) and the EBHOM's estimation of average optimal monthly hydropower generation in the same period at White Rock Hydropower Plant, part of the Sacramento Municipal Utility District (SMUD) reservoir system. Assuming a fixed energy head, unregulated water runoff is linearly related to available energy runoff. On the basis of the no-spill assumption, total annual energy generation for a given hydropower plant (from observed energy generation data) in a given year equals the annual available energy runoff at its location in that year, and only the seasonal distributions differ. Accordingly, the monthly distribution of energy runoff in each year was assumed to be the distribution of mean monthly runoff for the period 1928 to 1949. Monthly energy runoff was computed (for use in equation (4)) on the basis of the monthly runoff distribution given by the hydrologic record where annual energy runoff equals the annual hydropower generation. Monthly revenue curves were based on information from California Independent System Operator Open Access Same-Time Information System Web Site for the year 2005 (Hourly average energy prices, California Independent System Operator Open Access Same-Time Information System (OASIS), 2007, http://oasis.caiso.com/). The nonlinear optimization problem was solved by linear programming through piecewise linearization of the concave revenue function.

[28] Generally, the difference of historical and modeled values is due to the mismatching runoff, hydropower generation, and price data sets used, and nonenergy hydropower operations such as maintaining spinning reserves. The summer generation peak found by the model (in September) is due to the high price of energy in September

Table 1. Summary of Results of the Two Methods Used to Study the SMUD System[a]

Method	Scenario				
	Historic	GFDLA2	GFDLB1	PCMA2	PCMB1
		Annual Runoff Change With Respect to the Historical Case			
NA	NA	−52%	−37%	−12%	−3%
		Annual Generation (GWh)			
EBHOM	1,672	793	1,055	1,428	1,605
Traditional	2,647	1,217	1,655	2,246	2,546
		Annual Generation Change With Respect to the Historical Case			
EBHOM	NA	−53%	−37%	−15%	−4%
Traditional	NA	−54%	−37%	−15%	−4%
		Annual Revenue (million $)			
EBHOM	118	71	87	105	115
Traditional	167	98	122	150	163
		Annual Revenue Change With Respect to the Historical Case			
EBHOM	NA	−40%	−26%	−11%	−3%
Traditional	NA	−41%	−27%	−10%	−2%

[a]The two methods are EBHOM and the traditional hydropower optimization of *Vicuna et al.* [2008]. For the SMUD system, see *Madani et al.* [2008]. NA means not applicable.

in the data set, which might not be true for the period 1985–1998. Often hydropower generators presell their power through long-term contracts with fixed prices and control only that portion of hydropower generation not already sold.

7. Reliability

[29] To examine the reliability, advantages, and limitations of the proposed method, EBHOM was tested against an existing hydropower optimization model on California. Therefore, in a collaborative-comparative study, *Madani et al.* [2008] studied the climate change effects on hydropower generation of Sacramento Municipal Utility District's (SMUD) hydropower facilities in California through two different approaches. The studied high-elevation hydropower system, known as the Upper American River Project (UARP), is in El Dorado and Sacramento counties within the Rubicon River, Silver Creek, and the South Fork American River drainages, on the west slope of the Sierra Nevada Mountains in California. The UARP has 11 reservoirs which can hold over 524 million m^3 (425,000 acre-feet) of water, 8 powerhouses which can generate up to 688 MW of power, and about 45 km (28 miles) of power tunnels/penstocks [*Madani et al.*, 2008].

[30] In the first approach, the energy storage capacities, corresponding to each hydropower facility, were estimated through the NSM. Then EBHOM was developed for the each hydropower facility. In the second approach, a traditional hydropower optimization model [*Vicuna et al.*, 2008] was developed for the whole system. This second (physically based) model used the conventional volumetric units and restricted the operations to physical constraints (i.e., turbine and reservoir capacity) and operational constraints (e.g., minimum in-stream requirements). This model assumed no head-storage effect (storage does not significantly affect hydropower head in high head units) which made the model formulation linear when off-peak and on-peak pricing were not considered. To incorporate the on-peak and off-peak pricing, the formulation of the model was modified on the basis of the introduced energy price representation method (equations (17)–(20)) which made the model nonlinear (similar to EBHOM). While EBHOM had a perfect foresight into future hydrologic conditions and used a monthly time step, the second model used a moving horizon approach [*Hooper et al.*, 1991] with variable time steps (daily to monthly) which gave the model a partial foresight at different temporal resolutions into future inflow conditions [*Vicuna et al.*, 2008].

[31] The two models where solved through piecewise linearization to estimate the monthly hydropower revenues between October 1984 and September 1998 under four climate change scenarios and the historical scenario. The climate change scenarios used were the outputs from the variable infiltration capacity (VIC) model, a macroscale, distributed, physically based hydrologic model [*Liang et al.*, 1994]. The climate scenarios considered in the analysis corresponded to the projections of the NCAR PCM and GFDL CM2 climate models run under the greenhouse gas emission scenarios SRES A2 and SRES B1 [*Cayan et al.*, 2006]. Generally, a decline in spring and summer streamflows and an increase in streamflows in winter would be expected under these climate warming scenarios. In terms of extreme daily conditions, higher flows during winter time and lower flows in spring and early summer months were projected. Table 1 shows the results of the two models. Although the two methods predicted different generation and revenues for different climates, they predicted the same changes in generation and revenue from the historical case. The annual generation predicted by EBHOM exactly equaled the historical annual generation, as EBHOM had used the historical annual generation as an annual energy inflow to the system. The conventional method overestimated the annual generation and revenues, however, its predicted generation reduction under climate warming scenarios matched the results of EBHOM.

[32] Figure 5 shows the recorded average monthly generation and the predicted average monthly generation from both methods for historical inflows. One reason for the mismatch between the modeled and recorded generations is the use of 2005 hydropower prices for the whole modeling period (1985–1998) because of the unavailability of earlier price data. Although there was a difference between actual

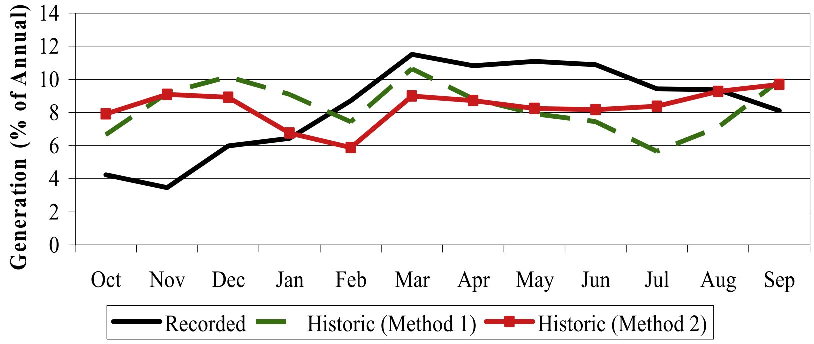

Figure 5. Recorded and modeled monthly hydropower generation of the SMUD system (methods 1 and 2 correspond to EBHOM and the traditional hydropower optimization model of *Vicuna et al.* [2008], respectively) [*Madani et al.*, 2008].

and simulated generation, both models suggested a comparable monthly generation pattern, similar to the average monthly hydropower price pattern in 2005. Both models overestimated generation in September–January and underestimated generation in other months.

[33] Figures 6a and 6b show the predicted average monthly hydropower generation distribution (equation (9)) through both methods for different climate scenarios and recorded average monthly hydropower generation during the study period. Both models predicted similar monthly generation patterns under each climate scenario.

[34] Figures 7a and 7b show the estimated end of month used storage capacity from both methods for different climates. Figure 7 indicates what percentage of storage capacity (energy storage capacity in Figure 7a and volumetric storage capacity in Figure 7b) used at the end of each month. Although the units are different, both methods predicted the same pattern of changes under different climate scenarios. Although, spills are expected with climate change, Figures 7a and 7b may imply that the storage never reaches the maximum capacity and there is no spill. However, what is shown here is the maximum capacity of the whole system. Thus, while one reservoir spills, other reservoirs might not be full. On the basis of the results, not all reservoirs fill at the same time. Thus, the used storage capacity never reaches 100% of the systemwide storage capacity. A comparison of Figures 7a and 7b implies that in general, more systemwide storage is used with EBHOM. This is for two reasons. First, the NSM underestimates system storage capacity. Second, the NSM considers energy storage capacity as that portion of the total capacity actually used for energy generation. Thus, it ignores that portion of the actual capacity which might be used for other purposes or remain unused in the average year. NSM also does not allow carryover storage (Figure 7a). However, the traditional model allows for carryover storage, and with a foresight of future inflow conditions might use carryover storage to supply generation under dry future hydrologic conditions. For the traditional model, monthly storage never reaches zero.

[35] Since NSM underestimates storage capacities, the energy-based method underestimated the adaptability of the studied system to climate change. EBHOM optimizes monthly hydropower generation on the basis of its perfect foresight into future hydrological pattern. This kind of management is impossible in practice as there is always some risk in reservoir operation decisions because uncertainty in future hydrologic and price conditions. Despite these drawbacks, EBHOM's results were very similar to those of the traditional optimization model. Both methods predicted almost the same changes in annual generation and revenues under climate warming scenarios and predicted the same trend of monthly generation and monthly water (energy) storage. EBHOM's simplicity and the amount of detailed information required for modeling a given hydropower system are its advantages over traditional volumetric-based models. Since modeling large high-elevation hydropower systems like that in California with more than 150 hydropower plants through traditional methods would be tedious and costly, EBHOM can be used in

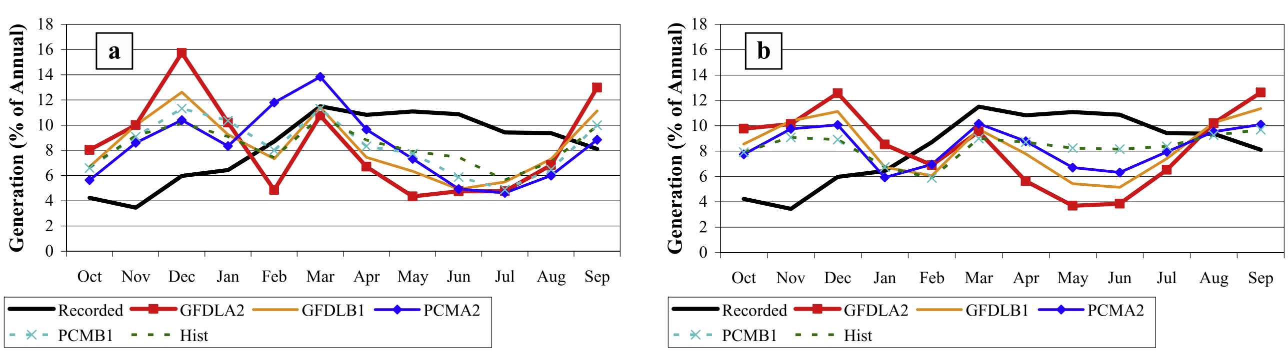

Figure 6. Hydropower generation of SMUD system under different climate scenarios: (a) EBHOM results and (b) traditional optimization results [*Madani et al.*, 2008].

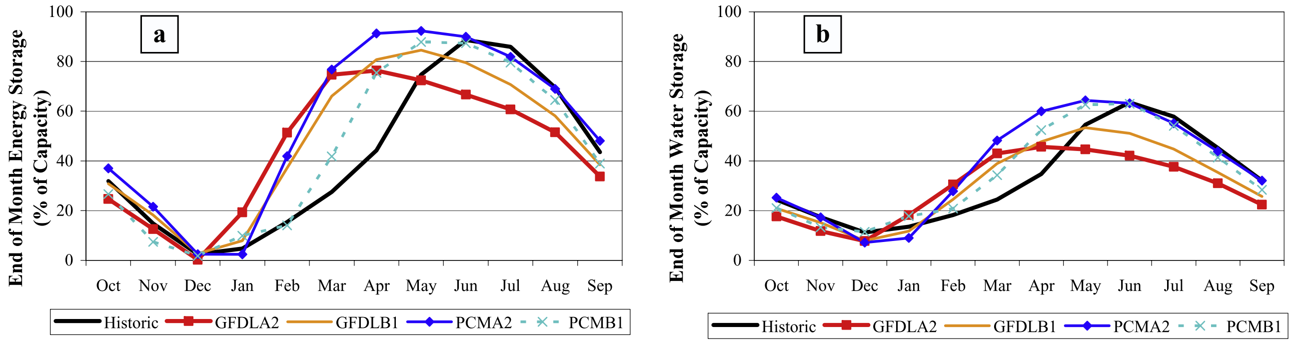

Figure 7. End of month used storage in the SMUD system: (a) EBHOM results and (b) traditional optimization results [*Madani et al.*, 2008].

preliminary studies of the high-elevation hydropower systems in California. A detailed traditional optimization model can provide information on more detailed local operations including water storage in the reservoirs, spills in different months of the year, and minimum downstream flows. EBHOM is useful for studying large hydropower systems when there is less interest in details of the system and the traditional method is preferable when more detail is needed for particular systems.

8. Estimation for 137 Plants in California

[36] EBHOM was applied for modeling the high-elevation hydropower system in California. One hundred fifty-six (156) high-elevation (above 305 m or 1,000 feet) hydropower plants in California were identified. Monthly hydropower energy generation information from U.S. Energy Information Administration Databases for the period 1985 to 1998 was used to estimate average monthly hydropower energy generation of each power plant. Instead of using the name plant capacity of each hydropower plant, the maximum actual monthly generation over the 1982–2002 period was used as the monthly generation capacity. For estimating energy storage capacity available for each hydropower unit, mean monthly generation and mean annual generation were estimated. Mean monthly values were then normalized into percent of mean annual generation (equation (9)) to characterize the average seasonal distribution of energy generation at each unit. Since runoff patterns vary by elevation, three elevation ranges are considered (305–710 m or 1,000–2000 feet, 710–915 m or 2000–3000 feet, and above 915 m or 3000 feet). Monthly runoff data for the study period were obtained from several USGS gauges representing these elevation ranges, selected in consultation with the former California Department of Water Resources (DWR) chief hydrologist. For each elevation range, mean monthly and mean annual runoffs were estimated. Mean monthly values were then normalized into percent of mean annual runoff (equation (8)) to characterize the average seasonal distribution of available water runoff for each elevation range. Energy storage capacity of each unit was then estimated using the NSM. Real time hourly energy prices were obtained from the California ISO OASIS for the year 2005 (OASIS Web site, http://oasis.caiso.com/) to derive convex monthly revenue curves.

[37] EBHOM was used to estimate the optimal historical monthly generation. The EBHOM for each plant was solved in Microsoft Excel (through piecewise linearization) with "What's Best," a commercial solver package for Microsoft Excel. With the cyclic EBHOM formulation, each run for one reservoir for each year under a given hydrology takes 3–4 s. Historical generation data was complete for 137 high-elevation plants for the period of 1985–1998. The piecewise-linear optimization model was run for each year to find revenue-maximizing monthly reservoir storage and energy generation for these 137 power plants with the historical hydrology. Assuming no over-year storage, release decisions in each year are independent. Figure 8 shows the range of the estimated energy storage and generation capacities of the studied high-elevation hydropower plants.

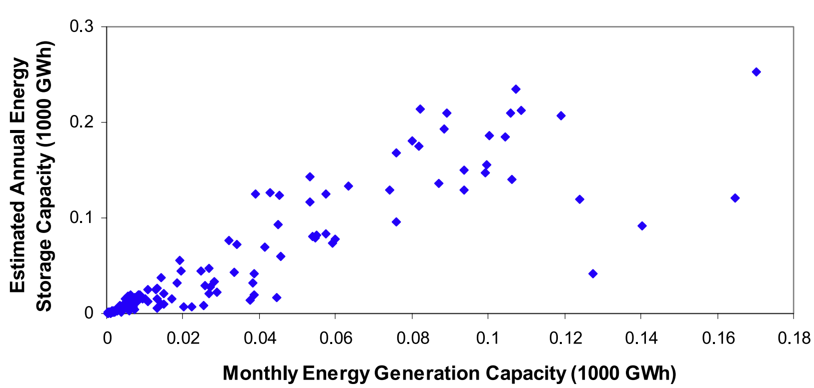

Figure 8. Range of the estimated energy storage and generation capacities of the 137 studied high-elevation hydropower plants in California.

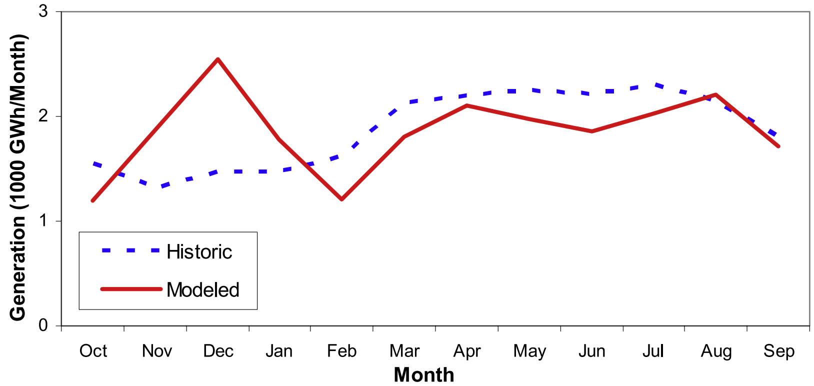

Figure 9. Comparison of historical average monthly electricity generation and optimal average monthly electricity generation (found by EBHOM) of 137 hydropower units in California in the 1985–1998 period.

The annual energy storage capacities of almost half of the studied power plants are at least 1.5 times larger than their monthly generation capacity, which provides some flexibility in operations. For more than 100 studied power plants, energy storage capacity exceeds one month of generation capacity.

[38] Figure 9 shows the historical and modeled average energy generation of 137 hydropower plants for the period 1985 to 1998. (The analysis has not been done for an average year but for 14 years of hydrologic (energy inflow) annual variability, spanning dry, wet, and average years. The results are reported as averages over the 14 year period for which 14 model runs were required). The optimized generation for the historical climate differs from historical observations (the dashed curve in Figure 9). Differences arise from a variety of factors, including nonhydropower operating factors, different hydropower prices for the recorded years, nonenergy hydropower operations such as spinning reserves, and the foresight of the model regarding incoming flows. Another reason for divergence between the EBHOM's results and the observed generation is application of a representative annual hydrograph for each elevation band rather than locally measured inflows for each year. Generation results are price driven and follow the California ISO energy price trends in 2005.

[39] Figure 10 shows the average optimized end-of-month energy storage in all reservoirs combined. EBHOM suggests that reservoirs reach their minimum storage level by the end of December in preparation to capture inflow from winter precipitation and spring snowmelt. On average, reservoirs fill by June and gradually empty for energy generation over summer when prices are higher and there is little natural inflow. Thus, under historical conditions, refill starts in January and drawdown starts in July.

[40] Figure 11 indicates the average shadow prices of annual energy storage and generation capacities (the average increase in annual revenue per unit of annual capacity expansion) for all 137 reservoirs for the study period. Figure 11 shows the average increase in annual revenue (y axis) per MWh annual energy storage/generation capacity expansion for corresponding number of power plants (x axis). For instance, increase in annual revenue is less than \$10 per MWh energy storage capacity expansion for 18 of the studied power plants. For most plants, one unit of annual storage capacity expansion is more beneficial than one unit of annual generation capacity expansion as water can be stored in the reservoir in low-value months to be released in summer when energy prices are higher. Although expansion of storage and generation capacities is always beneficial, expansions might not be justified because of expansion costs. In some cases, where hydropower plants are in series and draw on the same upstream reservoir, the value of expanding that reservoir would be the sum of storage expansion values for all downstream plants. Since

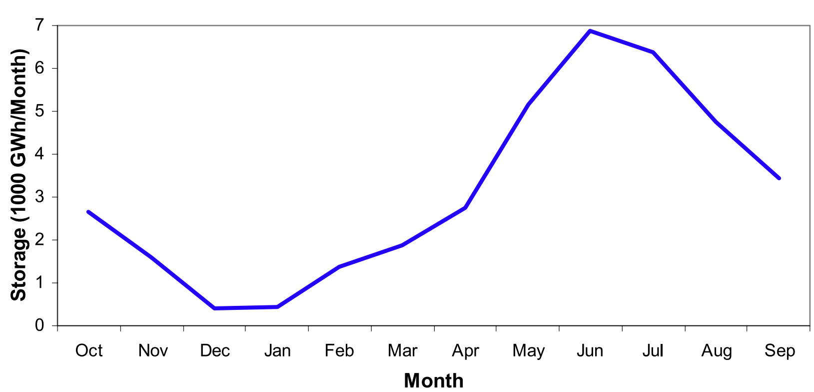

Figure 10. Average modeled total end-of-month energy storage (found by EBHOM) of 137 hydropower units in California in the 1985–1998 period.

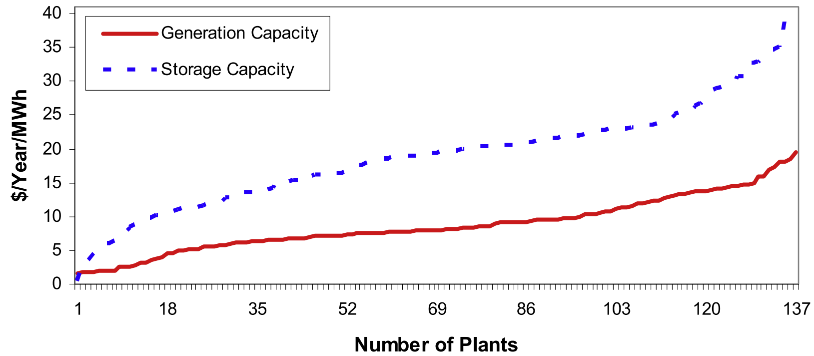

Figure 11. Average shadow prices of monthly energy generation and energy storage capacities (found by EBHOM) of 137 hydropower units for California in the 1985–1998 period.

the NSM (no-spill method) tends to underestimate energy storage capacities, the values for storage capacity expansion are probably high estimates.

9. EBHOM Applications

[41] Generally, an EBHOM can be applied in any hydropower system operation study where there is relatively little effect of storage on head and there is an interest in the big picture of the system and details are of lesser importance (e.g., large-scale policy, preliminary planning, and adaptation studies). Some potential applications are discussed below.

[42] Climate warming is a hydropower concern in regions with significant snowmelt runoff, such as California. High-elevation hydropower systems in California rely on snowpack for seasonal storage of precipitation, which makes those systems more vulnerable to climate warming [*Vicuna et al.*, 2008; *Madani and Lund*, 2007]. EBHOM is convenient for studying climate change effects on large-scale hydropower systems. Monthly runoff (energy inflow) can be perturbed for various climate change scenarios. The effects of several climate scenarios can be calculated quickly for broad system-scale studies to accompany more local conventional hydropower optimization studies [*Vicuna et al.*, 2008].

[43] Effects of energy demand/pricing changes on hydropower generation and resulting downstream flows also can be studied using EBHOM. Greater energy demand increases energy prices. Currently, electricity is more expensive in summer and winter months from cooling and heating. Energy demand can change for various climatic, economic, technologic, policy, or market reasons. Climate warming also can reduce winter energy use and prices (for heating) and increase use and prices in summer (for cooling). Energy prices also might change from changes in supply. For instance, more energy generation from earlier snowmelt might reduce energy prices in early spring. Energy prices also can change with long-term changes in energy use technologies (e.g., for heating and cooling), economic growth, energy market conditions (availability of nonhydropower energy supplies), energy conservation, or energy regulatory policies. The effects of changes in energy prices on hydropower generation can be studied conveniently by developing representative revenue curves (similar to Figure 3) for conditions of interest.

[44] In some parts of the world, large-scale expansions of hydropower storage and generation are being contemplated. EBHOM formulations can be used to explore and identify promising types and locations of power plant expansions, employing the Lagrange multiplier (shadow price) results for energy storage and generation capacity constraints.

[45] A final application of this type of coarse model might be for seasonal energy production and market studies and forecasts. A coarse EBHOM can quickly give seasonal energy planners and schedulers insights into when and how much hydropower is likely to be produced over a coarse seasonal horizon, although operators are likely to have access to more detailed proprietary models.

10. Limitations

[46] The no-spill method (NSM) for estimating energy storage capacity should be applied to the systems where there is little or no spill in many years and little over-year storage. Nevertheless, the NSM will tend to underestimate storage capacities and therefore also underestimate the adaptability of the hydropower system to hydrologic and economic conditions. More detailed studies could improve estimates of energy storage capacities.

[47] For this application to California, we assume that inflow distributions adhere to fixed seasonal patterns, which seem reasonable for California's Mediterranean climate. This EBHOM is formulated without environmental flows. Environmental constraints sometimes restrict the flexibility of operations and introduce trade-offs between hydropower generation revenues and ecosystem conservation benefits. These tend to be less for high-elevation reservoirs, but will probably increase with time. Environmental constraints could be included as minimum releases or as changes in the objective function or the frequency distribution of prices.

[48] EBHOM is a deterministic model and optimizes generation on the basis of perfect foresight for seasonal inflows and the frequency distribution of prices. Such management is impossible in practice, because of imperfectability of forecasts of hydrologic and price conditions. Long-term generation contracts also will affect operations.

11. Conclusions

[49] This study introduced an innovative simplified approach for exploring the performance of high-elevation hydropower systems without detailed information on volumetric storage capacity, inflow, turbines, or geometric configuration. Estimation of energy storage capacity is from seasonal shifts of energy inflows to generation, energy

inflows from seasonal inflow distributions, and generation capacity from maximum observed generation rates.

[50] The goal of this study was to explore an approach for studying extensive multifacility high-head hydropower systems with minimal available information and efficient computation. This approach is used to represent 137 high-elevation (high-head) units in California. Although the developed method required some simplifying assumptions, EBHOM was found reliable when tested against an existing hydropower optimization model in a collaborative-comparative study of climate change effects on hydropower generation of Sacramento Municipal Utility District's (SMUD) hydropower facilities in California. EBHOM can be applied in high-elevation hydropower operation studies examining climate change effects and adaptations for hydropower generation, exploring the effects of electricity demand and pricing changes on hydropower generation, early planning for extensive capacity expansions, and seasonal energy forecast and scheduling studies. EBHOM's simplicity and the amount of detailed information it requires for modeling a given hydropower system are its advantages over traditional volumetric-based models. EBHOM should be useful for studying large hydropower systems when there is less interest in system details.

[51] The contributions of this work are as follows: (1) an energy unit–based model (Energy-Based Hydropower Optimization Model or EBHOM) of single-purpose hydropower generation systems, requiring little model development effort for low-detailed modeling, (2) the no-spill method (NSM) for estimating energy storage capacity, (3) a price-frequency method of better representing hourly energy prices in models with larger time steps, (4) a cyclic storage formulation to decrease calculation time and cost, and (5) a simple approach for developing a good representation of an extensive system with little time or resources for policy and adaptation studies for various purposes.

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