International Conference on Hydroinformatics

2014

Short-Term Optimization Model With ESP Forecasts For Columbia Hydropower System With Optimized Multi-Turbine Powerhouses

Jery R. Stedinger

Sue Nee Tan

Christine A. Shoemaker

Jonathan R. Lamontagne

Steven B. Barton

SHORT-TERM OPTIMIZATION MODEL WITH ESP FORECASTS FOR COLUMBIA HYDROPOWER SYSTEM WITH OPTIMIZED MULTI-TURBINE POWERHOUSES

JERY R. STEDINGER, SUE NEE TAN, CHRISTINE A. SHOEMAKER, JONATHAN LAMONTAGNE (1), STEVEN B. BARTON (2)
(1): School of Civil and Environ. Engineering, Cornell University, Ithaca, New York, USA
(2): Short-term Operations Planning, Bonneville Power Administration, Portland, Oregon, USA

This paper describes efforts to develop a computational laboratory to evaluate the advantages of alternative stochastic short-term scheduling models for a 10-project subsystem of the federal reservoirs on the Columbia and Snake River systems operated jointly by the U.S. Army Corps of Engineers, the Bureau of Reclamation, and the Bonneville Power Administration (BPA). The analysis considers variable time step lengths increasing from 4 to 8 to 24 hours; economic and non-economic turbine dispatch with operational constraints; and inflow and load uncertainty (reflecting wind generation) through use of Ensemble Streamflow Predictions (ESP) augmented to include load uncertainties (ESLP). Synthetic ESLPs will be generated for the model testing effort. A project goal is to evaluate the advantages of alternative representations of economics, operations, and uncertainty subject to all of the operational constraints, both physical and those that result from environmental concerns.

INTRODUCTION

Hydroelectric generation is the major source of energy in the Pacific Northwestern region of the United States. The Federal Columbia River Power system consists of 31 hydropower projects and some thermal generation plants jointly operated by the U.S. Army Corps of Engineers, Bureau of Reclamation, and the Bonneville Power Administration (BPA). This system is the largest producer of power in the Pacific Northwest, providing about 60% of the power for the region. However, power production is not necessarily the highest priority in the operation of the reservoir system. The three Federal agencies are legally bound to operate to meet the needs for navigation and operations that preserve endangered aquatic life [1]. These and other constraints (e.g. recreation) may conflict with policies that seek to maximize the benefits from energy generation. Efficient operation of the system is an important economic, environmental, and social issue.

The number of hydropower projects and the complexity of the problem call for use of efficient numerical optimization techniques. However, it is unclear which descriptions of objectives and representations of uncertainty will be the most efficient in terms of improving systems decision recommendations, better representing system operation and uncertainties, computational requirements. This paper describes the development of a computational laboratory to be used to better understand the consequences of using different model structures, objectives, and representations of uncertainty.

OPTIMIZATION PROBLEM FORMULATION

The analysis focuses on the 10 key federal projects in the Federal Columbia River Power System. BPA dispatches and markets the power produced by these projects. The total generation capacity for the 10-project system is about 20 GW. Figure 1 provides a schematic of the system and reports average travel times. When considering short-term operations planning (releases within a day), the time of flow between projects can be important.

With our model the objective is to maximize the value of hydropower generation, as represented in Equation (1) below.

$$\max\left\{ J = \sum_t F_t\left(E_t\right) \right\} \text{where } E_t = \sum_i GH_t^i - Load_t \qquad (1)$$

The decision variables are the flow through the powerhouse, flow through the spillway, and the storage in each project for all time steps. In Equation (1), $F_t(\cdot)$ is a function that describes the value of hydropower generation (total revenue or costs avoided). E_t is the net generation of the hydropower system (total generation minus assigned system load) sold on the market. $\sum_i GH_t^i$ is the total system generation from all projects *i* at time *t*, and is a function of the optimized multi-turbine powerhouse generation function for project *i*. $Load_t$ is the assigned load served by the 10 modeled Federal projects at time *t*.

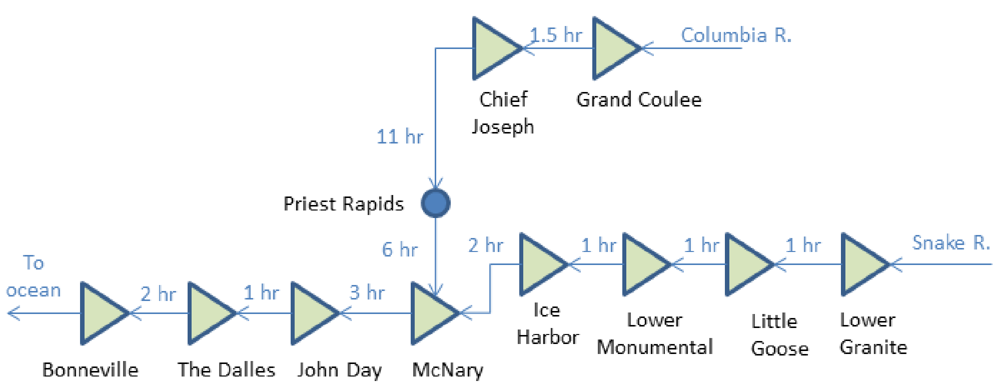

Figure 1. Schematic of the Federal 10-reservoir system on Columbia-Snake Rivers

The optimization is subject to the following constraints:

1) Conservation of mass is to be observed at all times. The storage continuity equation is expressed as Equation (2).
2) Reservoir storage should be within its bounds at all times and at all projects.
3) The storages at the end of the horizon should equal the ending-target storage.
4) Flows through the powerhouse are bounded by minimum powerhouse flow requirements and powerhouse flow capacity.
5) "Controlled" releases using the spillway are bounded by the minimum spillway flow required for fish passage, and the spillway flow cap for total dissolved gas.

6) “Forced spills” using the spillway that exceeds the spillway flow cap for total dissolved gas flows should be nonnegative.
7) Grand Coulee forebay elevation drawdown is limited over a rolling 24-hour period.
8) The federal system should provide enough flow volume for the non-federal projects between Chief Joseph and McNary to meet flow minimums downstream of Priest Rapids.

The optimization problem in Equations (1) and **Error! Reference source not found.** subject to the constraints listed above is nonlinear in the objective function due to the nonlinearities in the powerhouse generation function. These nonlinearities are important and thus a nonlinear programming solver (Matlab’s FMINCON) is employed.

Value of hydropower generation

Overall wholesale day-ahead energy prices are affected by streamflow levels in the region, by the current and future availability of thermal generation, and by tie-line capacity from British Columbia to California. The value assigned to hydropower produced by the system can be valued simply by BPA total system revenue, or more appropriately by its social value described by the willingness-to-pay of energy purchasers reflecting the total cost of energy displaced by BPA production [2]. Because the Federal Columbia River Power System provides a large share of the power production in the Pacific Northwest, the power BPA produces often affects the regional market price. We model this effect with a demand function such as that in Figure 2. The demand function indicates that as BPA sells more and more energy, the price of energy decreases. In fact at some point, the market cannot absorb more energy and the price of energy drops to zero.

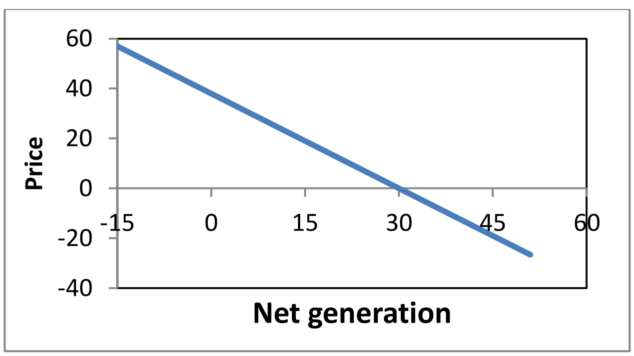

Figure 2. The wholesale price for power in day-ahead market depends on BPA net generation

Flow routing model

The time of flow from Grand Coulee, the upper reservoir on the Columbia, to Bonneville, the lowest reservoir on the Columbia, is approximately 24 hours. Thus when considering within-day operations, flow transit times can be important. In order to ensure that water that flows through the system is neither gained nor lost in the routing process, Equation (2), the mass balance constraint must be satisfied at all reservoirs at all time steps.

$$S_t^i = S_{t-1}^i + \sum_{\tau} C^i{}_{\tau} R^i{}_{t-\tau} + I^i{}_{t,inc} \tag{2}$$

where

S_t^i is the storage in project i at time t

C_{τ}^{i} is the *i*th row in the τth lagged routing coefficient matrix corresponding to the *i*th project
R_{t}^{i} is the total release from project *i* at time *t*
$I_{t,inc}^{i}$ is the incremental flow into project *i* at time *t*

The flow routing in the optimization model considers the travel times between the 10 reservoirs through the use of the lagged routing coefficient matrix C_{τ} in Equation (2), based on the method described by Labadie [3].

In the matrix C_{τ}, the rows correspond to the upstream project and the columns correspond to the downstream project. The outflows from each reservoir at time *t* are represented as -1 down the main diagonal of the lag $\tau = 0$ matrix . The number of lags considered depends on the time step of the model. The off diagonal elements are numbers between 0 and 1 that describes the proportion of flows from the upstream project that arrive at the downstream project at time lag τ. Assuming a constant outflow over the time step, the proportion of the flow the downstream reservoir receives at time step *t* is the ratio of the difference between the time step length and the travel time to the length of the time step. The remainder arrives at the next time step.

Variable time steps

Variable time steps over the modeled planning horizon are used to decrease the number of decision variables. The use of the variable time steps reflects the fact that the need for detailed operating plans decreases with time, and forecast precision degrades as the forecast horizon increases; therefore it is attractive to use a coarser time step in later time steps. A concern is if a model with a longer time step accurately reflects the future value of water. The model of operations using a 24-hour routing time step can be formulated to include within-day operations to represent the value of generation realistically, while employing 24-hour flow routing. Tejada-Guibert et al [4] illustrate including a range of within month operations in a monthly model.

Powerhouse generation functions

Large BPA storage projects can include many turbines of different types; for example, Grand Coulee has 27 turbines of 4 types. Deciding which turbines to run and the optimal flows through each turbines is not a trivial task. Traditionally, this problem was solved using mixed-integer linear programming. For example, Li et al. [5] use a three-dimensional interpolation technique to reduce required computational effort.

Precomputed powerhouse functions reduce the decision space by aggregating the generation of individual turbines into an optimal powerhouse generation curve. Thus, we need only work with the total flow through the powerhouse without scheduling individual turbines. There are many feasible dispatch solutions that can be generated to optimize the production of power given the flow through the powerhouse. Shawwash et al. [6] use dynamic programming to derive optimal powerhouse flows for each increment in plant loading, forebay, and for each turbine unit availability combination. Our calculations for the powerhouse functions generates a simple description of what is possible if we make the assumption that the last unit dispatched is allowed to operate only part of the time.

With Economic Dispatch, each unit in the powerhouse is grouped into distinct types as determined by their generation functions. These types are dispatched in decreasing order of efficiency. The main assumption is that as each new turbine is loaded, it runs "part time," for some proportion of the time step at its most efficient operating point, while other turbines of the same type operate the entire time at their most efficient operating point. When there is more than one turbine operating, only the latest turbine runs part time. When all the turbines of the most efficient type are all running full time, they are all pushed beyond their most efficient operating point until their marginal generation rate is equal to that of the next most efficient type. Then, additional turbines of the next most efficient type are loaded in the same manner.

Fish Dispatch differs from Economic Dispatch in that the dispatch order is not necessarily economic. This is because certain units are prioritized to improve flow patterns in the vicinity of the dam, or to provide attraction flow for fish ladders. The dispatch order of the unit types may not be in decreasing order of efficiency. However, power generation from the powerhouse is still optimized to the extent possible, by selection the flow through each turbine that is operating – only the dispatch order is specified. Sometimes over the entire dispatch order, or at least portions of it, the fish-priority dispatch allows an economic dispatch and loading.

DETERMINISTIC OPTIMIZATION RESULTS

The model describes the operation of the 10-reservoir federal system for T days, using 4 hour, 8 hour and 24 hour time steps as prescribed by the user. To demonstrate the utility of the 24-hour routing with on- and off- peak releases, the deterministic model was also run for a 10-day planning period in August using the three models summarized in Table 1. Model M8 uses 8-hour time steps, model M24-1 uses 24-hour time steps with a single power-house release that is constant over the 24 hours, and model M24-2 uses 24-hour time steps with "on-peak" and "off-peak" powerhouse releases. The remarkable result is that model M24-2 returned exactly the same system generation policy as model M8 (see Figure 3), using a fraction of the computation effort. In contrast, Figure 3 and Table 1 show that model M24-1 produced a very different system generation policy, and under estimated possible benefits by 21%.

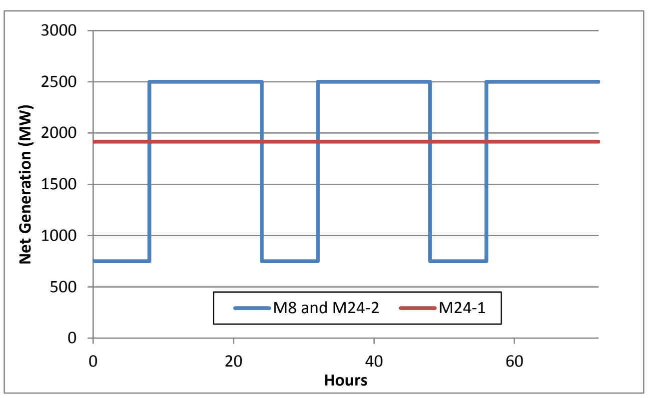

Figure 3. Net Generation versus time for three model configurations for the first 3-days of a 10-day planning horizon in August

We can draw two important conclusions from this example. First, the M24-1 model does not capture important system operations, because it does not reflect the diurnal nature of the load and price. Second, the M24-2 model can capture the benefits achieved with the M8 model without modeling the flow routing on a sub-daily basis. This is of particular interest for models with variable time steps. Such models are predicated on the assumption that the releases in the next *d* days are of most interest, and rely on the 24-hour model to provide a good approximation of system operation after day *d* though not necessarily the optimal release schedule. This example suggests that failing to model the sub-daily operation in a 24-hour model can cause the model to misrepresent system benefits.

Table 1. CPU time and system benefit for several model configurations optimizing operation of a10-reservoir subset of the Federal Columbia River Power system over a 10-day horizon in August.

Model	CPU time (s)	System benefit (million $)
M8	931	5.11
M24-1	155	4.01
M24-2	268	5.11

Improvements of 21% will not be typical of all cases. For example, a trial run for October observed no improvement of model M24-2 over M24-1. This was because the “on-peak” and “off-peak” energy prices did not vary much during that period, so an average daily price was sufficient. This suggests that the use of the M24-2 model rather than the M24-1 model will be of most value when the difference between “on-peak” and “off-peak” prices are large.

STOCHASTIC OPTIMIZATION

Ensemble streamflow predictions (ESPs) are forecasts which represent the uncertainty distribution of future inflows as a series of scenarios which might occur. Previous works have explored the use of ESP forecasts in hydropower operations optimization [7],[8]. The proposed two-stage stochastic optimization model uses a simple branching structure to incorporate ESP forecasts and a short-term deterministic forecast into a short-term planning model, as illustrated in Figure 4. Similar models have been used by Pacific Gas & Electric [9] and Charles Howard [10].

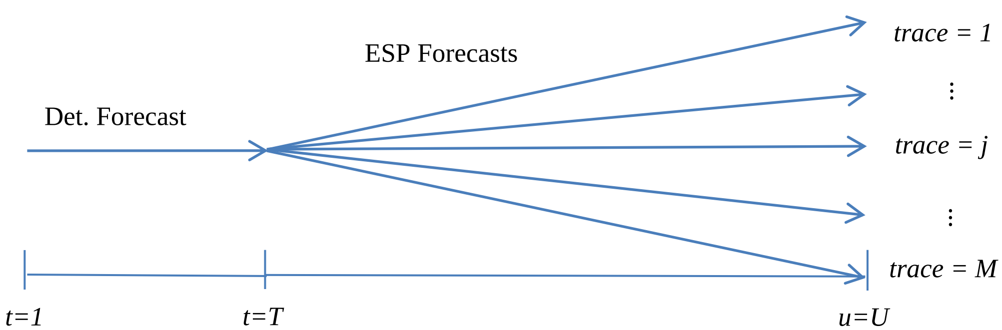

Figure 4. Use of an event tree to describe system inflow uncertainty

In the first stage, a single forecast is used while in the second stage, M different ESP traces are used; this means that in the second stage there are M unique inflow forecast scenarios. The objective of the two-stage stochastic model is given in equation (3).

$$\max\left\{\sum_{t=1}^{T} F_t + E\left[\sum_{u=T+1}^{U} F_u\right]\right\} = \max\left\{\sum_{t=1}^{T} F_t + \sum_{j=1}^{M}\sum_{u=T+1}^{U} F_u(j)p(j)\right\} \quad (3)$$

where

t is the time index of the first-stage,
T is the terminal time index of the first-stage,
F_t is the objective function value in time step t,
u is the time index of the second stage,
U is the terminal time index of the second stage,
j is the index of ESP traces in the second stage,
M is the total number of ESP traces, and
$p(j)$ is the probability of transitioning into scenario j in stage-two from stage-one.

The stage-one model objective is $\sum_{t=1}^{T} F_t$, whereas the stage-2 model objective is $E[\sum_{u=T+1}^{U} F_u]$. The stage-one model and each stage-two trace will have a unique set of independent constraints which are basically identical to those described in the deterministic model. A key addition is a set of constraints which tie the stage-one and stage-two models together. For example, there are flow routing constraints which ensure that all of the releases in stage-one are accounted for in stage-one or the appropriate period in stage-two.

A major concern with the model in Equation (3) is that the number of decision variables is linear in M, which might cause solution of the model to be computationally impractical if M is large. One approach to reducing the effort needed to solve the model is to use Benders Decomposition, which is well suited to this application [9],[11],[12].

Another approach to reducing the computational burden of solving Equation (3) is to reduce the number of traces M. Faber and Stedinger [13] and Faber [14] reduced the number of ESP traces used by a hydropower planning model from 42 to 10 without affecting the quality of the resulting optimal policy. This was accomplished by grouping traces with similar hydrographs, and representing each group by a characteristic trace. Each characteristic trace was then given the combined probability of the entire group in the subsequent stochastic optimization. The model in equation (3) will allow for similar examination of the value of different representations of uncertainty for the BPA system. The results reported by Faber and Stedinger [13] and Faber [14] were for a single reservoir only.

CONCLUSION

This paper discusses development of a computational laboratory for BPA to help understand the tradeoffs between different model structures, objectives, and representations of uncertainty. Variable time steps with finer time steps in the beginning and coarser time steps later speed up model runs while providing near-term resolution of system operations. Modeling on- and off-peak releases with a 24-hour time-step model can in some cases can result in the same energy production schedule as a model with routing of flows with a finer time step.

Ensemble streamflow predictions are a way of representing uncertainty in the system dynamics. A two-stage stochastic programming model was formulated. To reduce the computational burden of the optimization from having many traces, the number of traces can also be reduced in a systematic fashion while retaining the precision with which unusual flow series are represented; of interest is the effect of forecast descriptions on release decisions.

REFERENCES

[1] U.S. Army Corps of Engineers, U.S. Bureau of Reclamation, and Bonneville Power Administration, "Federal Columbia River Power System," August, (2003).

[2] Russell, C.S., "Applying Economics to the Environment", Oxford University Press, Oxford, (2001).

[3] Labadie J. W., "Optimal Operation of Multireservoir Systems : State-of-the-Art Review," J. Water Resour. Plan. Manag., vol. 130, no. 2 (2004), pp. 93–11,.

[4] Tejada-Guibert J. A., Stedinger J. R., and Staschus K., "Optimization of Value of CVP's Hydropower Production," J.WaterResour Plan.Manag., Vol. 116, No. 1 (1990), pp 52–70.

[5] Li X., Li T., Wei J., Wang G., and Yeh W. W.-G., "Hydro Unit Commitment via Mixed Integer Linear Programming : A Case Study of the Three Gorges Project , China," IEEE Transactions on Power Systems, Accepted, (in-press).

[6] Shawwash Z. K., Siu T. K., and Russell S. O. D., "The B . C . Hydro Short Term Hydro Scheduling Optimization Model," IEEE Trans. Power Syst., vol. 15, no. 3 (2000), pp. 1125–1131.

[7] Faber, B.A. and Stedinger, J.R., " Multi-reservoir Optimization with Ensemble Streamflow Forecasts using Sampling Stochastic Dynamic Programming, ASCE 2006 Operations Management Conference, Sacramento CA, Vol. 1, (2006).

[8] Kim, Y-O, Eum H-I, Lee E-G, and Ko, I. H., "Optimizing Operational Policies for a Korean Multireservoir System using Sampling Stochastic Dynamic Programming with Ensemble Streamflow Prediction", J. Water Resources Planning and Management, vol. 133 no. 1 (2007), pp. 4-14.

[9] Jacobs, J., Freeman, G., Grygier, J., Morton, D., Schultz, K., Staschus, J., Stedinger, J.R., and Zhang, B., "Stochastic Optimal Coordination of River-basin and Thermal Electric Systems (SOCRATES): A System for Scheduling Hydroelectric Generation Under Uncertainty", Annals of Operations Research, Vol. 59, (1995), pp. 99-133.

[10] Howard, C., "Experience with probabilistic forecasts for cumulative stochastic optimization," Proc. American Water Resources Association Symposium, Reno Nevada, November (1992).

[11] Benders J.F., "Partitioning procedures for solving mixed-variables programming problems", Numer. Math, Vol. 4, No. 1 (1962), pp. 238-252.

[12] Lasdon, L.S., "Optimization theory for large systems", Reprint of 1970 Macmillan ed., Dover Publications Inc., (2002).

[13] Faber, B.A. and Stedinger, J.R., "Reservoir optimization using sampling SDP with ensemble streamflow prediction (ESP) forecasts", Journal of Hydrology, Vol. 249, No. 1-4, (2001), pp. 113-133.

[14] Faber, B.A., "Reservoir Optimization Using Sampling Stochastic Dynamic Programming (SSDP) with Ensemble Streamflow Prediction (ESP) Forecasts", PhD thesis, Cornell University, Sept. 2000.