International Conference on Hydroinformatics

2014

Efficient Methods For Optimizing Hydropower Under Uncertainty

Timothy Michael Magee Jr.

Edith A. Zagona

Mitch Clement

11th International Conference on Hydroinformatics
HIC 2014, New York City, USA

EFFICIENT METHODS FOR OPTIMIZING HYDROPOWER UNDER UNCERTAINTY

TIMOTHY M. MAGEE. JR. (1), EDITH A. ZAGONA (1), MITCH CLEMENT (1)
(1): Center for Advanced Decision Support for Water and Environmental Systems (CADSWES), University of Colorado at Boulder, U.S.A.

There are several sources of uncertainty in scheduling hydropower: reservoir inflows, power generation, demand and value, and the value of water remaining in storage at the end of the planning horizon. RiverWare is an object oriented modeling tool widely used for the operations and planning of large and small systems of reservoirs. Typically, short term optimization of hydropower is complicated by the need to meet a wide variety of prioritized non-power constraints and RiverWare is designed to satisfy these constraints to the extent possible. We present four different approaches that use deterministic methods combined with uncertainty models to efficiently optimize scheduling using RiverWare. 1. Load following reserves were used for coordinating uncertain wind generation with hydropower generation to meet uncertain load. 2. Chance constraints were used to model uncertain hydrologic inflows and inflows from dams controlled by other organizations. 3. Operating policies were designed to dynamic balancing of reservoirs with limited storage and bottlenecks to retain system flexibility while meeting anticipated load fluctuations. 4. Network stochastic programming was used to model alternative hydrologic inflow scenarios that depend on the hydrologic state. Each approach was motivated by and tested on a real system with one or more sources of uncertainty.

INTRODUCTION

Uncertainty in scheduling hydropower comes from several sources: hydrologic uncertainty, power uncertainty, and the future value of water remaining in storage at the end of the planning horizon. Hydrologic uncertainty stems from both natural inflows and releases from upstream reservoirs that are controlled by other parties. These releases are uncertain because these reservoirs are also subject to similar uncertainties. Power uncertainty arises in three related forms: uncertainties in generation both from hydropower and non-hydropower sources, uncertainties in demand, and uncertain prices between utilities. Both hydrologic and power uncertainties affect hydropower in the short term and the long term. In a short term planning model the long term uncertainties are manifested in the future value of water remaining in storage at the end of the planning horizon.

RiverWare is an object oriented modeling tool widely used for the operations and planning of large and small systems of reservoirs. [1] Typically, short term optimization of hydropower is complicated by the need to meet a wide variety of non-power constraints. These non-power constraints usually have higher priority than power constraints. At times, hydrologic conditions may prevent these constraints from being fully satisfied. In such cases, the objective becomes to satisfy these constraints to the extent possible. Some non-power are more important than others and can be expressed in a priority order. RiverWare models these priorities with a preemptive goal program that maximizes the satisfaction of these non-power constraints and optimizes hydropower objectives with the remaining degrees of freedom. [2]

In the next section we present four different approaches that use deterministic methods combined with uncertainty models to efficiently optimize scheduling using RiverWare: load following reserves, chance constraints, dynamic balancing of reservoirs, and network stochastic programming. Each approach was motivated by and tested on a real system with one or more sources of uncertainty. In the final section we discuss the relative advantages of each approach.

UNCERTAINTY APPROACHES

Load Following Reserves

Load following reserves can be a useful tool when a system has to meet not only an uncertain load, but also when generation sources are also highly uncertain. For example, in the Pacific Northwest hydropower and wind generation are significant sources of generation, and integrating them to meet uncertain load while meeting habitat constraints for aquatic species is challenging. A properly designed load reserve can incorporate both load uncertainty and wind generation uncertainty when scheduling hydropower.

The authors conducted a study [3] on the effect of different wind penetration levels on hydropower operations and used load following reserves as part of that study. The study modeled the scheduling process as a combination of a “scheduling” run that set aside power flexibility with a combined wind and load reserve and a succeeding “operations” run that used the reserve as actual wind generation and load fluctuations were realized.

The load following reserve for each time period is scheduled to assure guarantee capacity to absorb variability in net load and net load forecast error. Assuming that these two components of load following are uncorrelated, the combined requirement is calculated by taking the root sum of squares of the individual requirements, Eq. (1). For the variability component, Eq. (2), the requirement is set equal to the absolute value of the hourly net load change corresponding to an exceedence probability of 0.995. Similarly, the reserve requirement is calculated as the absolute error magnitude associated with an exceedence probability of 0.995, Eq. (3).

$$LF_t^{req} = \sqrt{\left(LF_{NL\Delta}^{req}\right)^2 + \left(LF_{NLFE}^{req}\right)^2} \tag{1}$$

$$P\left(\left|L_t^{net} - L_{t-1}^{net}\right| \le LF_{NL\Delta}^{req}\right) = 0.995 \tag{2}$$

$$P\left(\left|\varepsilon_t^L + \varepsilon_t^W\right| \le LF_{NLFE}^{req}\right) = 0.995 \tag{3}$$

The load following reserve requirement is removed in the operations run to simulate the use of the reserve capacity to meet the actual load as it deviates from the forecast.

Chance Constraints

Chance constraints can be used in within math programming optimization to limit the probability of a constraint violation.[4,5] We applied these constraints specifically to limit the probability of violating pool elevation constraints caused by uncertain hydrologic inflows and upstream inflows from dams controlled by other organizations. In theory, the releases from upstream dams could be considered deterministic. In practice, the organizations controlling them respond to the types of uncertainty we have listed.

The chance constraints were applied to five Mid-Columbia river projects owned by three public utility districts which are operated by a "Central" control. These projects have limited storage and typically have daily filling and drafting cycles. The projects also have lag times that range from 1 hour to several hours. Uncertain inflows take two forms for these projects: side flows and upstream reservoir releases. Upstream of these projects are two federal projects controlled by Bonneville Power Administration (BPA) as one part of their management of the federally owned facilities on the Columbia River and its tributaries. While there is some coordination between BPA and Central, they are still independently operated and the Central operators experience uncertain deviations from BPA's original schedule.

As an initial method, we assumed that the combined forecast deviations of side flows and BPA releases are

1. Proportional to the forecasted inflows, and
2. Independent in time.

With the second assumption and use of the central limit theorem, we approximate the uncertainty in total future inflows as a normal distribution with variance growing linearly with time, i.e. a standard deviation that grows as a square root function of time. For an hourly time step model we can write:

$$Uncertain\ Volume_t = p \times Inflow\ Forecast\ Total\ Daily\ Volume_t \times \sqrt{\frac{t}{24\ hr}} \qquad (4)$$

where p is a user parameter to control risk. For example, a value of 0.1 will lead to an uncertain volume for the next day equal to 10% of the forecast daily volume. The parameter p can be set based on the operator's desired probability of violating elevation constraints.

The next step is to allocate this uncertain volume to the five projects. Central control preferred that this volume be allocated on an equal restriction on elevation constraints across the five projects. Thus, the chance constrained maximum and minimum elevations at each project are

$$Chance\ Maximum\ Elevation_{r,t} = Deterministic\ Maximum\ Elevation_{r,t} - \Delta_{max}$$
$$Chance\ Minimum\ Elevation_{r,t} = Deterministic\ Minimum\ Elevation_{r,t} + \Delta_{min}$$

where Δ_{max} and Δ_{min} are calculated so that the combined changes in elevation at the projects equal the uncertain volume.

Dynamic Balancing Of Reservoirs

The Mid-Columbia system used to illustrate chance constraints in the previous section is also useful for illustrating another concept for managing uncertainty, dynamic balancing of reservoirs. The key features are the lags between reservoirs and the daily cycling of reservoirs to meet the peaks and valleys of load. Central control can potentially face a situation where the reservoirs as a whole may have the theoretical capacity to increase or decrease reservoir storage to respond to changes in inflows or load, but in practice the capacity is located in the wrong place within the system to meet the need. If the system also has imbalance in the turbine capacity in terms of flow, natural bottlenecks can increase the severity of this problem.

Qualitatively, the approach to prevent this situation is clear. Sequence the drafting of reservoirs such that when load is increasing toward a peak the reservoirs are drafted in an upstream first to downstream manner, and when coming down off of a peak, the reservoirs fill in an upstream first to downstream manner. At the daily minimum and maximum load, the reservoirs should be relatively equally drafted. This approach maximizes flexibility during the maximum and minimum load periods when the system flexibility is least. The order of the reservoirs for drafting and filling provide the water and storage capacity for the system to adapt to change.

This qualitative reasoning can be translated into constraints. For time steps with an increasing load, each reservoir's Outflow is constrained to be greater than or equal to that reservoir's Outflow at the previous time step and the next downstream reservoir's Outflow at the current time step. For time steps with a decreasing load, each reservoir's Outflow is constrained to be less than or equal to that reservoir's Outflow at the previous time step and the next downstream reservoir's Outflow at the current time step. For time steps that are a local peak in the load, the reservoir's Outflow must be greater than or equal to that reservoir's Outflow at the previous time step, and for valleys, the reservoir's Outflow must be less than or equal to that reservoir's Outflow at the previous time step. Finally, at a lower priority, the reservoirs are equally drafted at the time steps of each daily minimum and maximum load.

In a real time setting, these constraints can be further prioritized with the constraints for early time periods preceding those for later periods. Such an approach focuses on positioning the system for flexibility in the short term over flexibility in the long run.

Network Stochastic Programming

The previous three approaches deal with uncertainty during the planning horizon of a run. Equally important is the uncertain value of water remaining in storage at the end of the planning horizon. For reservoirs with significant storage, the value of using water for generation during the planning horizon must trade off against the value of saving the water for future generation. (When reservoirs have less storage, there is less to tradeoff and an elevation target may suffice.) The value of water remaining in storage at the end of the planning horizon depends on both the uncertainty of future inflows and to a lesser extent the uncertainty of the value of future generation. We describe a method to incorporate the uncertainty of future inflows. [6]

Historically, two approaches have dominated the stochastic optimization of reservoirs: Stochastic Dynamic Programming (SDP) and Stochastic Programming with Recourse (SPR), sometimes referred to as Stochastic Dual Dynamic Programming (SDDP). Both of these methods have their uses and limitations. SDP performs well for many time steps when used with a system with a small number of reservoirs, but suffers from the "curse of dimensionality" when modeling a larger system. [7] In contrast, SPR performs well for large systems with a small number of time steps, but also suffers from a curse of dimensionality as the number of time steps increases. [8] Briefly, SPR starts with a single model for the initial time step, branches to a recourse model for each scenario at the second time step and each of these model branches with each successive time step resulting in a tree of connected models. The "communication" between the recourse models is the future value of water in storage under the different scenarios. Thus, the end result solving the multiple models is both the value of water in storage at each reservoir at each node in the tree and the optimal operations for each arc in the tree. In math programming parlance these are the dual and primal values respectively.

Network stochastic programming (NSP) is a third alternative that is methodologically closer to SPR than SDP. The major difference is that the separate branches of the SPR are combined to form a smaller set of "states" which have similar hydrologic forecasts. Thus, the tree structure is converted to a network, illustrated in Figure 1. This particular network has three hydrologic forecast states for each time period: low, middle, and high.

The different hydrologic states allow for the correlation of hydrologic inflows from one time step to another. If the inflows were uncorrelated for a given system, a single node would suffice for each time period. For a system with more complex correlation of inflows more nodes may be required. For example, a system with reservoirs sufficiently geographically separated that they have two different hydrologic states might use nine nodes at each time step.

This approach has been tested with an 8 week model of the Tennessee Valley Authority (TVA) reservoir system. For each week the entire TVA system was optimized for maximum power value at a 6-hour time step. Each arc in Figure 1 corresponds to one of these models, and each arc was solved multiple times as part of an iterative algorithm similar to SPR. All but the five largest reservoirs were modeled with fixed ending elevations. The remaining five reservoirs constitute the majority of longer term storage for the system. (The method is not affected by the number of reservoirs, but this did allow for easier testing and refinement of the algorithm.)

NSP was compared against the existing method for calculating the value of water in storage at TVA. If these results from February and March are extrapolated to the rest of the year, a

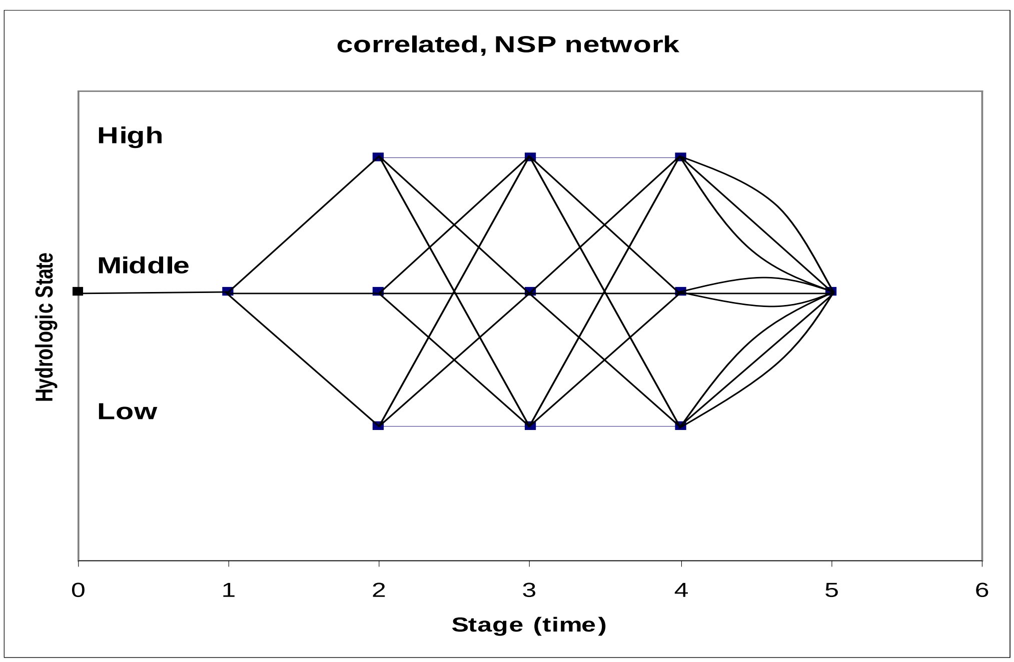

Figure 1: Network Stochastic Programming Network

change in methods could be worth an improvement of approximately $2 million per year. However, it is entirely possible that the value may be very different for other seasons.

DISCUSSION OF APPROACHES

All four approaches are efficient and use deterministic solution methods to optimize in the presence of uncertainty. However, the methods have value in different settings.

Load following reserves are efficiently implemented and add little computational burden to an optimization model. The largest benefits are realized when a highly uncertain generation source such as wind is a significant part of the generation portfolio.

Chance constraints are an easy way to limit the probability of important constraints being violated. The constraints provide a rational basis to generate an optimal deterministic solution that naturally becomes more conservative in later time periods in order to limit the probability of constraint violations.

Dynamic balancing of reservoirs is useful when reservoirs are lagged and have limited storage space. The approach maximizes flexibility during periods of maximum and minimum generation when a system typically has the least flexibility.

The first three methods optimize for uncertainty during the planning horizon, while NSP models the uncertain value of water in storage at the end of the planning horizon. The method is valuable when there are many reservoirs with significant storage capacity and many time steps are needed to adequately model scenarios.

REFERENCES

[1] *Zagona, E.A., Fulp, T.J., Shane, R., Magee, T. and Goranflo, H.M., "RiverWare: A Generalized Tool for Complex Reservoir System Modeling", Journal of the American Water Resources Association, Vol. 37, No. 4(2001),pp 913-929.*

[2] *Eschenbach, E.A., Magee, T., Zagona, E., Goranflo, M. and Shane, R., "Goal Programming Decision Support System for Multiobjective Operation of Reservoir Systems", Journal of Water Resources Planning and Management, Vol. 127, No. 2 (2001), pp 108-120.*

[3] *Clement, M., Magee, T., and Zagona, E., "A Methodology to Assess the Value of Integrated Hydropower and Wind Generation", accepted by Wind Engineering*

[4] *Charnes, A. and Cooper, W.W., "Chance-constrained programming," Management Science, Vol. 6 (1959), pp 73-79.*

[5] *Charnes, A. and Cooper, W.W., "Deterministic equivalents for optimizing and satisfying under chance constraints," Operations Research, Vol. 11 (1963), pp 18-39.*

[6] *Emmert, J.D., "Network Stochastic Programming for Valuing Reservoir Storage", Thesis, University of Colorado at Boulder (2005)*

[7] *Bellman, R.E., "On the Theory of Dynamic Programming" in Proceedings of the National Academy of Sciences, USA, Vol. 38 (1952), pp 716-719*

[8] *Periera, M.V.F., and Pinto, L.M., "Stochastic Optimization of a Multireservoir Hydroelectric System – A Decomposition Approach", Water Resources Research, Vol. 21 (1985), pp 779-792*