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USING MULTI-SCALE UNCERTAINTY INFORMATION AND SPECIFIC FORECAST SKILL TO IMPROVE RESERVOIR OPERATIONS

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Optimization of reservoir operations to time series of forecasted inflows are constrained by a set of multiple objectives that span many time scales, however the temporally evolving skill of the forecasts are usually not considered in the objective functions. For example, a flow forecast time series extending from 1 day to 6 months consists of a medium range flow forecast that draws its skill from initial conditions and weather forecasts and a seasonal flow forecast that relies on the initial conditions only. The skill of the medium range flow forecast is the daily and aggregated values with a range of uncertainties that increases with lead time, while the seasonal flow forecasts only have skill in the monthly volumetric values with a range of uncertainties that is large, but predictable. Unfortunately, the impacts of temporally evolving skill and uncertainty on reservoir operations and operational risk are unknown, which may leave significant room for improvement.

To explore this question we conduct a set of optimization experiments of reservoir operations at the snowmelt dominated Gunnison River Basin in Colorado. Each optimization experiment uses the same ensemble flow forecast, which is a merged ensemble medium range forecast with an ensemble seasonal forecast, but utilizes a different set of weights that are applied to the medium and seasonal scale objectives (which are to maximize revenue and environmental performance). By comparing the weighted set of optimizations to a non-weighted optimization, we are able to isolate the impact of the skill and uncertainty of the forecasts on reservoir operations. We conclude by using the results to develop a functional relationship between the skill and uncertainty in the forecasts to the objective weights and as a basis to calculate operational risk.

INTRODUCTION

Water resources management in large river basins has become very complex as the stakes increase and competition for limited amounts of water increase. Typically, simulation software is used to aid water managers in planning and optimizing everything from water allocation to reservoir operations. To model basin-scale operations, inflow forecasts are required at the model boundaries. In addition, operational constraints and objectives are usually defined at multiple time scales and for multiple purposes. The required inflow forecasts are produced by a chain of model simulations implying a cascade of uncertainties. Climate forecasts with either some skill, such as global forecast models, or with no skill, such as from climatology resampling, mean that a hydrology model needs to generate an ensemble of flow forecasts to cover all potential future scenarios. Consequently, the water management model is then run as many times as they are traces. In order to optimize the system objectives, the requirements are entered either as constraints or as values to be simultaneously minimized. Developers assign weights to the objectives in order to obtain a balance across all objectives or to give preferential consideration to one objective over another.

A seasonal ensemble flow forecast based on a resampling of past climate ensures that the "forecast" is unbiased and that the ensemble quantifies the climate uncertainties seen so far. Each trace is also equally probable. However, seasonal climate forecasts do not have a skillful sequencing and in snowmelt controlled basins the most skillful seasonal forecast product is the snowmelt volumetric content. The timing is highly uncertain which explains why the spread of the ensemble seasonal flow forecast is the widest during the snowmelt period. It is unclear how the large uncertainty in the timing of snowmelt impacts the optimization and the operational decision-making. Similarly, medium range weather forecasts are merged to ensemble seasonal climate forecasts in order to improve the first month volumetric content [1]. The temporal sequencing of the medium range flow forecasts is skillful, in contrast to the seasonal part. Like the seasonal forecast however, it is unclear how the optimization and decision making process is impacted by the higher skill of the first 5 days of the forecasts in comparison with the next following 5 days in a 10 day forecast, and with respect to the first month forecast. The goal of this paper is to develop a decision making approach that will leverage from the multiple scenarios generated by basin scale optimization and explore how objective functions can be tuned to better take advantage of when the skill of the inflow forecast is best.

APPROACH

The study utilizes the Water Use Optimization Toolkit (WUOT) for the analysis. The WUOT is a Department of Energy funded project that consists of an integrated set of tools that are designed to provide specific, yet overlapping functionality to optimize hydroelectric power operations and water use planning. The tools are briefly described as follows:

1. The Enhanced Hydrologic Forecasting System (EHFS) tool is a spatially distributed modeling system that provides daily to seasonal ensemble inflow forecasts for use by the seasonal hydro-systems analysis, day-ahead and real-time scheduling, and environmental performance analysis tools [2].
2. HydroSCOPE is a coupled one-dimensional reservoir and river routing model that simulates reservoir and river temperatures, power production, and revenue, as well as downstream river conditions, as a function of inflows, meteorological conditions, and power and water demand. The system includes multi-objective optimization for evaluating tradeoffs between operational and environmental factors. The tool also allows users to balance seasonal and multi-seasonal forecasts of energy demand and water availability/water demand against power generation capacities, operational constraints, competing water users, and environmental performance [3].
3. The Index of River Functionality (IRF) tool incorporates environmental objectives into the toolset by computing the environmental performance measures associated

with a time-series of hydropower operations for various habitats at specific locations across a basin. IRF scores typically are a function of flow, habitat, and population dynamics. The IRF allows users to evaluate differences in the environmental performance of various operating scenarios [4].

4. The Conventional Hydropower Energy and Environmental Resource System (CHEERS) modeling system creates schedules for power generation, ancillary services (regulation up and down, spin reserves, and non-spinning reserves), and water releases. These schedules are driven by multiple objectives, simultaneously solving for energy and environmental goals [5].

This paper utilizes the EHFS, HydroSCOPE, and IRF tool to conduct a set of optimization experiments of reservoir operations at the snowmelt dominated Gunnison River Basin in Colorado. Each optimization experiment uses the same seasonal ensemble flow forecast, which is a merged ensemble medium range forecast and an ensemble seasonal forecast, but utilizes a different set of weights that are applied to the medium and seasonal scale objectives (which are to maximize revenue and environmental performance). By comparing the weighted set of optimizations to a non-weighted optimization, we isolate the impact of the skill and uncertainty of the forecasts on reservoir operations.

The Gunnison River Basin

The Aspinall Unit (210 MW) of the Colorado River Storage Project is located in the South Fork of the Upper Gunnison River Basin. It consists of a series of dams: Blue Mesa, Morrow Point, and Crystal. During the irrigation season, a considerable percentage of the flow released from Crystal is diverted to the Uncompahgre Basin through the Gunnison Tunnel, directly downstream of Crystal. Further downstream, the balance of flow gains with inflow from several tributaries including the North Fork of the Gunnison and the Uncompahgre River before joining the Colorado River at the city of Grand Junction, Colorado. The area draining into the Aspinall Unit is about 10,000 km^2. Precipitation is relatively constant throughout the year, whereas temperature displays a strong seasonal cycle with temperatures below freezing from October to April [6]. Around 70% of the flow from the Gunnison River is from snowmelt [6, 7, 8]. April 1 snowpack can account for about 70% of the variability in annual runoff, indicating the utility of long lead flow forecasts [6].

Figure 1 shows a conceptualization of the Gunnison system as modeled by HydroSCOPE. The system consists of the three reservoirs (Blue Mesa, Morrow Point, and Crystal), and four river reaches. The forecasts from the EHFS tool are used to supply the five entry points into the model, the Gunnison River above Blue Mesa, an unnamed side inflow above Morrow Point, Cimarron Creek above Crystal, the North Fork of the Gunnision at river mile 29 below Crystal, and the Uncompahgre River at river mile 47 below Crystal. The lower boundary of the model is at the WhiteWater Gauge (USGS gauge 09152500), just south of Grand Junction at the confluence of the Gunnison and Colorado Rivers. A withdrawal from the model occurs just below Crystal Reservoir at the Gunnison Tunnel. An unforecasted inflow point (indicated as "ungauged" in Figure 1) is added to the last river reach to close the water balance at the White Water gauge. The ungauged inflows represent the accumulated inflow from numerous minor side inflows, and possibly groundwater discharges that are not captured at the resolution of the EHFS tool.

Inflow Forecasts

The seasonal ensemble flow forecasts used in this paper have been generated by the EHFS tool of the Water Use Optimization Toolset [9]. The tool leverages heavily from the Westwide Seasonal Forecast system developed at the University of Washington [10]. A time-series of observed meteorology is used to drive (spin-up) the hydrologic model during the nowcast. The spin-up period is long enough that the influence of assumed initial conditions (ICs) at the start of the simulation is removed and the model state reflects a best estimate of current conditions prior to the forecast. The Variable Infiltration Capacity (VIC) hydrology model [11] is then driven by an ensemble of meteorological forecasts to generate an ensemble of streamflow forecasts.

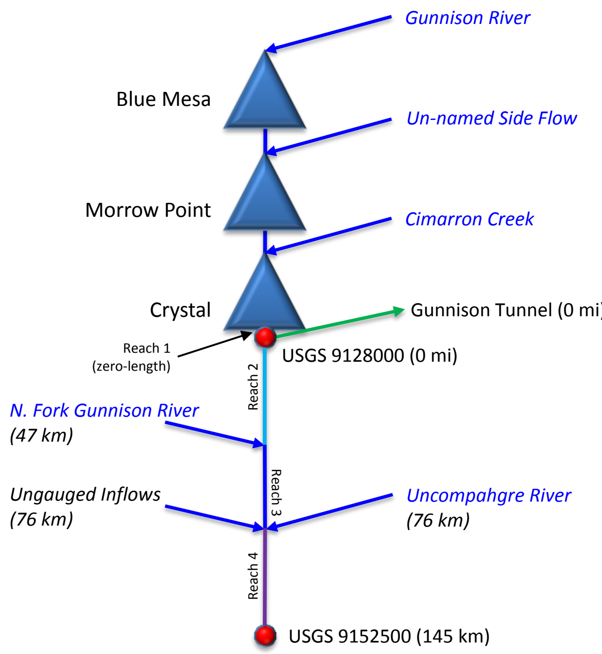

Figure 1. Conceptualization of the Aspinall Cascade and the Gunnison River as modeled in the Analysis. Labels in blue represent inflow boundary points for the EHFS ensemble forecasts.

Reservoirs with significant storage capacities rely on seasonal volumetric flow forecasts for their management. Shukla and Lettenmaier [12] have shown that improvement in seasonal climate forecast alone will lead to better seasonal hydrologic forecast skill throughout the year in most parts of the northeastern and southeastern U.S.; for the western U.S., the forecast skill is improved mainly during fall and winter months. However, specifically for the northwest U.S., initial conditions tend to drive seasonal flow forecasts in the spring and summer months, where a significant portion of U.S. hydropower is generated. The EHFS employs the Extended Streamflow Prediction (ESP) approach [13] used by the National Weather Service River Forecast Centers (NWSRFC) since the mid-1970s. The ESP relies on initial conditions and a resample of seasonal weather forecasts (traces) from previous years (1960-2010; 49 traces); this approach brings consistency between the nowcast and forecast systems.

The Global Forecast System (GFS) retrospective forecast dataset is used as the source of ensemble weather forecasts in the current implementation of the EHFS. The publicly available GFS forecasts provide a long-term dataset appropriate for training the downscaling approach and for the evaluation of the flow forecasts over a long period. This 30+ year retrospective forecast dataset (1979–2011) includes 14-day daily time-step forecasts at 2.5° spatial resolution derived from the 1998 version of the GFS [14]. An updated version of the dataset with a 1° spatial resolution using the current operational version of the GFS model has just been made available and is being integrated into the EHFS. Forecast variables from GFS include precipitation, daily average air temperature, and zonal and meridional wind components. An analog approach [15] is used to: 1) calibrate the information in the forecast ensemble (bias, probabilistic information); 2) downscale the forecast variables to the scale of the hydrology model; and 3) derive minimum and maximum temperature from the daily average temperature.

The extended 1950–2010 daily gridded meteorological dataset [16] at 1/8° spatial resolution as the source for analogs, therefore ensuring consistency with the nowcast period. The 15 members of the ensemble medium range weather forecasts are randomly paired with the 50 members of the seasonal ensemble climate forecasts creating a merged 50-member ensemble climate forecast. A statistical plot of the 50 member ensemble of inflows into Blue Mesa Reservoir is shown in Figure 2.

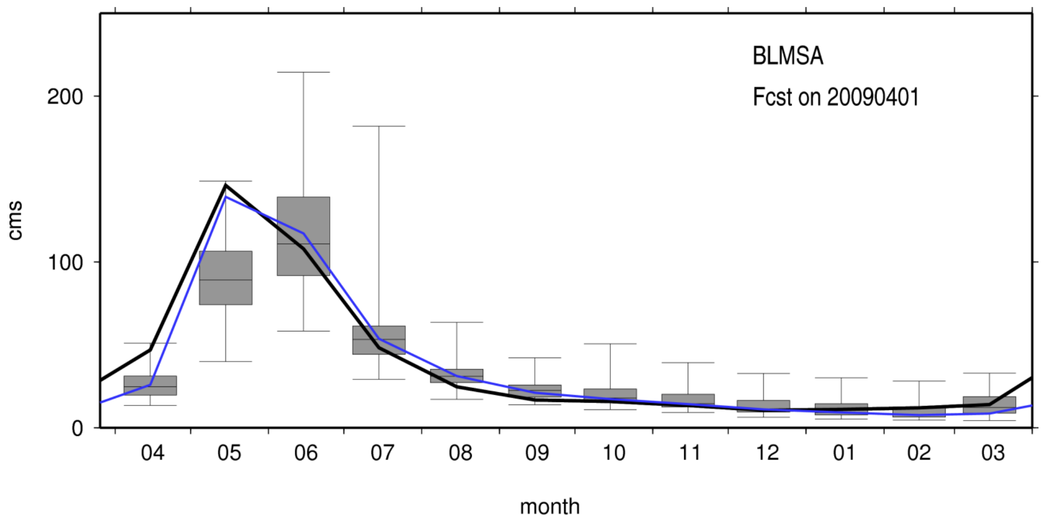

Figure 2. Twelve-month seasonal ensemble flow forecast for Blue Mesa issued April 1, 2009, with forecast flows to March 30, 2010. The black line shows observed naturalized flow, the blue line shows EHFS results based on observed meteorology, and the box and whisker plots show EHFS results based on ensemble meteorological forecasts. The boxes show the 25%, 50%, and 75% exceedance flows, while the whiskers represent the minimum and maximum ensemble members.

Optimization

The decision variables are a set of multipliers on the default release schedules for each reservoir in the system. Multipliers are used on the first 12 timesteps, the following 4 days, the following 3 weeks, and then the following 5 months. This allows the optimization a higher resolution of operational control in the early part of the simulation as compared to later in the simulation. The timestep is 6 hours. The default release schedule is calculated by the model with each ensemble case as a function of the operational logic and current system state.

HydroSCOPE utilizes the multi-objective genetic algorithm (MOGA) within the DAKOTA optimization software [17] to perform the optimization. As mentioned above, the optimization objectives are to maximize total revenue and maximize environmental performance. Three optimization sets were completed: 1) no objective weighting, 2) objective weighting, and 3) multiplier weighting. Recall that each set of optimizations use the same ensemble forecast but only differ in how the objectives are weighted. Optimization Set 1 refers to the default case where the objectives are weighted equally throughout the 6 month simulation period. The second Set refers to preferential weighting given to the early time objectives. In this case, the objectives for the first 3 days were weighted twice that as for the last 3 months. A Gaussian decline from three days to three months is used to weight the objective values between those times. Set 3 keeps the objective weights equal, but allows the optimization more freedom in optimizing the reservoir outflows during early times of the simulation as compared to late time. This was done to better incorporate the environmental performance score, which is a single integrated value over different timespans during the simulation, as opposed to a timestep by timestep summation that is used to calculate the total revenue. It should be mentioned that the calculated revenue is based on historical average monthly prices and distinguishes between peak and off-peak price periods. Each trace required 300 simulations to provide an adequate rendering of the relationship between the total revenue and IRF score, resulting in 15000 simulations per optimization Set.

RESULTS

The integrated risk of each trace within each optimization set was used as the comparison metric. The integrated risk is a measure of the consequence of using one particular trace for setting operations and then seeing any of the other 49 traces become reality. As used here, it provides a measure of which optimization set provides the user with the least amount of risk, or conversely, which optimization set minimizes our regret when reality provides us with something that is different than our forecast. To calculate risk, the consequence is multiplied by the probability of assuming one trace and then realizing another. The integrated risk for trace 'i' is the sum of the risk between trace 'i' and the other 49 traces. The consequence is defined as the average difference between the assumed and realized, revenue and IRF scores. If the difference between either of the metrics is less than one (meaning that the realized trace performed better), the difference is set to zero (i.e., there is no consequence). Probabilities are based on the exceedance probability of the total volumetric inflow of each trace and are defined as the inverse of the probabilistic distance between the assumed trace and the realized trace.

Figure 3 is a scatter plot of the integrated risk of each trace compared to the same trace in the corresponding optimization set. From the plot, it is evident that optimization Sets #2 and #3 are lower risk when compared to Set #1. This indicates that weighting the optimization, either through direct weighting of the objectives (Set #2) or by allowing more freedom to the optimization routine to alter early-time decision variables (Set #3) reduces our regret when reality ends up being different than what was forecasted. Comparing Set #2 to Set #3 (bottom left of Figure 3), there appears to be a slight advantage to Set #3, although the two sets are close enough that an argument for either Set could be made.

Figure 4 represents the 15000 simulations for each optimization Set as contours based on the relative point density between the normalized revenue and IRF scores. The plots are an indication as to the scattering of solutions that were explored by the optimization routine. A 'tighter' set of contours translates into less uncertainty in the optimized solutions, which in turn translates into less risk from the ensemble.

This analysis shows that there appears to be a clear relationship between the skill of the forecast and the risk of assuming a particular trace. Further analysis over different time spans and hydrologic and watershed conditions are needed to confirm this result.

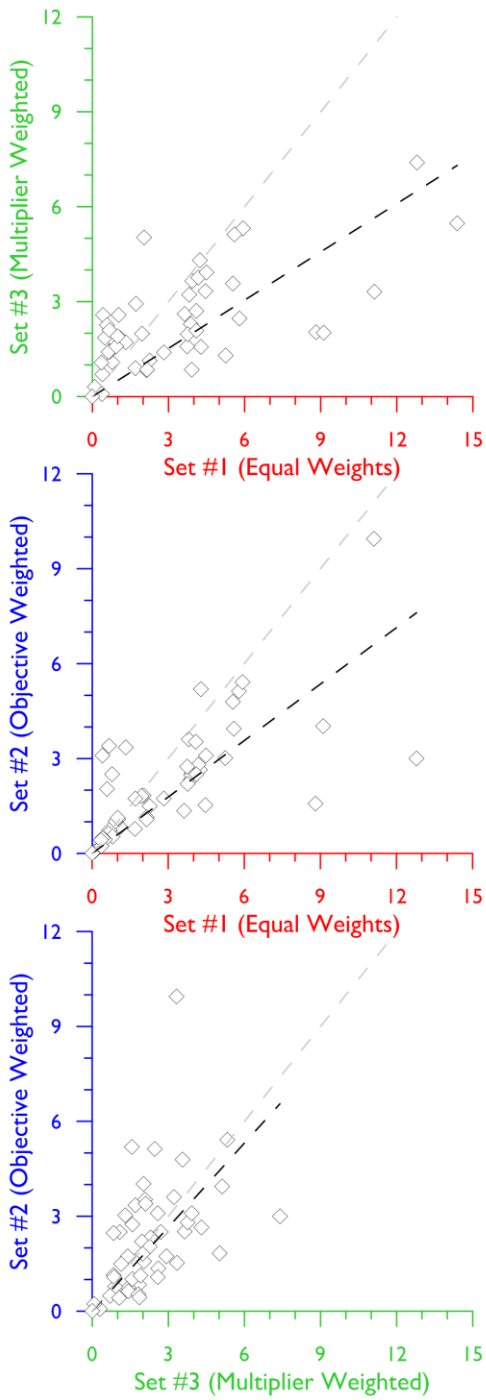

Figure 3. Trace by trace comparisons of the integrated risk of each optimization Set against each other. The black dotted line represents the linear trend between the two sets while the gray dotted line shows the 1:1 relationship. Sets #2 and #3 show a less integrated risk as compared to the default Set #1.

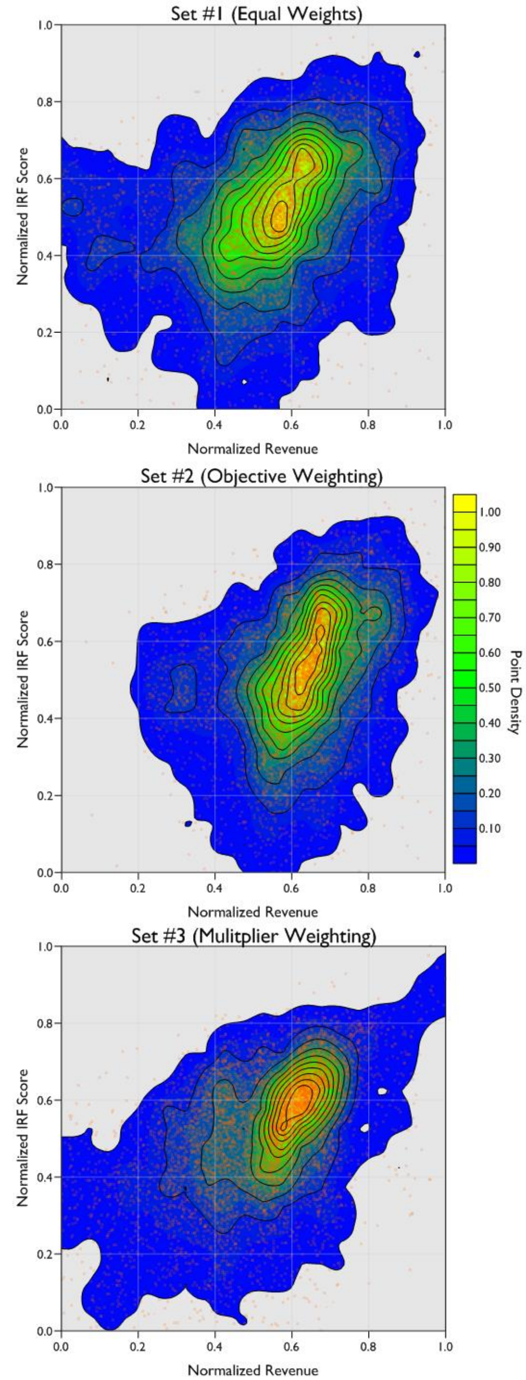

Figure 4. Contour plots of the 15000 simulations for each optimization Set. The point density refers to the normalized number of points that fall within a particular zone in the plot. Less 'spread' in the contours means less uncertainty in the optimization and thus less risk for the optimization Set.

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