Uncertainty Modeling in RiverWare™

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Abstract

In recent years, management considerations for reservoirs have been expanded to include environmental and recreational objectives. Uncertainty modeling contributes to better reservoir management by quantifying the uncertainties and determining the sources of significant uncertainty in predicting reservoir and river conditions which affect environmental habitats and recreational conditions. RiverWare employs a first-order, second-moment approach to modeling uncertainty. The method is described in this paper and applied to an example on Lake Mohave on the Lower Colorado River. Comparison of historical forecasts with observed data can provide managers with insight into operational policies which result in greater system uncertainty. Identifying these sources of uncertainty can guide managers in the development of future operational guidelines.

Introduction

Reservoirs have historically been built and managed for flood control, water delivery, and hydropower generation. Within the last 20 years, considerations such as habitat restoration, endangered species protection, water quality, recreation and aesthetics have become important management objectives as well. Operating a reservoir system with increasingly numerous objectives and constraints involves making trade-offs and assumptions of risk about management actions. In most cases, uncertainty plays a significant part in this decision-making process. Assumptions made in model development, spatial and temporal variations in parameters, boundary conditions, and external forcing functions can have significant impacts on the accuracy of physical model predictions. Considerations such as economic impacts of floods or drought, biologic impacts of fluctuating water levels or adverse water quality, impacts on recreation, and effects on revenue derived from the sale of hydroelectricity add uncertainty about management options. This kind of "institutional" uncertainty may manifest itself in many ways. It can occur when different agencies are charged with the operation of different parts of the same system, or when the operation of a system is based on forecasts of external influences (e.g., hydroelectric demand). This dichotomy in management may occur either spatially (i.e., from reservoir to reservoir within a river basin), or temporally (i.e., long-term release and daily operations not coordinated by the same management group). Uncertainty modeling can contribute to better reservoir management in two ways. First, it allows impacts on model predicitons from all sources of uncertainty to be quantified. Second, it helps identify which human controlled uncertainties are most deleterious to satisfying the largest possible set of operating goals.

Relatively little work in this area has examined the impacts of what we call "institutional" uncertainties. These are uncertainties which are a result of imprecise information about demands being placed on the system. For example, reservoirs which are used to generate peaking hydroelectric power are subject to the whims of electricity pricing, consumer demand, etc. In this paper, we employ a first order second moment (FOSM) approach for quantifying both physical and operational uncertainties of reservoir management. We show that the approach provides a useful tool for reservoir managers who are constantly weighing operational uncertainties against potential risk of violating operating constraints. The FOSM approach employs mean and variance equations derived from a Taylor Series expansion of the governing equations. The algorithms are implemented in the RiverWare (Zagona et al., 1998) modeling system. The coupling of FOSM methods with an object-oriented modeling system such as RiverWare provides significant benefits over uncertainty computations involving monte-carlo or other sampling based techniques. The FOSM method is applied to a case study from the Lower Colorado River (Lake Mohave).

In this paper, we provide an overview of the deveopment of the FOSM method, and discuss its implementation into the RiverWare modeling system. Then we present an example application using Lake Mohave on the Lower Colorado River. The case study shows how both physical and institutional uncertainties impact reservoir operations and the ability to meet operational constraints.

The FOSM Approach

The ideal measure of uncertainty is the probability density function (PDF). Models of hydraulic/hydrologic systems are typically so complex that analytical derivation of PDFs for each model variable is impractical. Values of "true" system uncertainties may be approximated in a number of ways. These approximations typically make simplifying assumptions about the relative magnitude of uncertain parameters, states and data inputs, and about the physical processes involved. Two of the more well-known approaches are those based on first-order second-moment methods, and the Monte Carlo methods. (For a comprehensive description of these and other approaches, the reader is referred to Yen et al., 1986 or Yen and Tung, 1993).

First-order, second-moment (FOSM) approaches estimate uncertainties based on the mean, variance, and covariance values of a system's uncertain parameters, states, etc. FOSM is often grouped with several closely related methods under the heading of Functional Analysis approaches (Bobba 1996). These methods include error analysis, uncertainty analysis, and confidence interval development. The commonality is in the use of first, second, and sometimes higher order moment equations developed from a set of system governing equations, and in the (usual) assumption that the uncertain elements of the system are normally distributed. The derivation of the moments typically involves Taylor series expansion or the equations around either mean or critical (i.e., failure point) values of one or more variables.

The FOSM approach has many variations in application. Simplification of stochastic inputs such that all variables are independent greatly simplifies the numerics. Other modifications to FOSM include the mean-value first-order second-moment (MFOSM) methods which expand the governing equations about their expected mean values to generate statistical moments. Advanced FOSM methods modify the point about which the stochastic variables are expanded. The method assumes that a more reliable estimate of risk can be achieved by expanding the values at the point which yields the lowest reliability for the design (Yen et al., 1986). Rosenblueth's (1975) method is another variation on the moment-based approach to uncertainty modeling. It can be used to generate moment functions of any order based on Taylor series expansion about mean values. The approach was later expanded to include asymmetrical distributions (Rosenblueth, 1981). The reader is referred to Jazwinski (1970) or Ditlevsen (1981) for a comprehensive review of these and other analytically based processes. Much of the existing literature deals with failure risks; i.e., dam failure, overtopping, structural integrity, etc. These problems are often static in nature, and the variables of concern are not variable in time. We are looking at a system in which variables are dynamic. The distributions of the errors about these variables may be assumed to be normal over a wide range of conditions. That is, the distribution of the variable itself is well defined (releases from reservoirs), and the uncertainty is assumed normally distributed. Commonly the uncertainties in reservoir systems are given by confidence levels, i.e., upper and lower bounds describing the range within which 95%, 90%, etc. of the values of the variable occur.

Governing Equations/Development of FOSM

We now present a simplified mass balance equation for reservoir storage and develop the FOSM uncertainty approximation from it. We use the following simplified differential equation to represent the dynamics of reservoir storage:

$$\frac{dV}{dt} = (I + H - Q - E - B) \qquad \text{Eq. 1}$$

where V is reservoir storage volume, I is inflow (mainstem), Q is outflow, H is local (hydrologic) inflow, E is evaporation, and B is bank storage. The discrete-time form of the above equation yields the following mass balance equation for reservoir storage:

$$V(t+\Delta t) = V(t) + \Delta t\left[I(t,t+\Delta t) + H(t,t+\Delta t) - Q(t,t+\Delta t) - E(t,t+\Delta t) - B(t,t+\Delta t)\right] \qquad \text{Eq. 2}$$

where the values of flow are averaged over the interval $(t, t+\Delta t)$. First order approaches for uncertainty modeling are developed from Taylor series expansion of the governing equations. The derivation begins by recasting the model variables in terms of an expected mean value and some unknown error term, which represents the difference between the "true" value of the parameter and the modeled mean value. This error term could be attributed to observation error, parameter estimation error, or errors resulting from generalizations or simplifications of the physical processes being modeled. Recasting the variables used in the above mass balance equation yields:

$$\begin{aligned} V &= \overline{V} + \delta V \qquad & I &= \overline{I} + \delta I \qquad & E &= \overline{E} + \delta E \\ Q &= \overline{Q} + \delta Q \qquad & H &= \overline{H} + \delta H \qquad & B &= \overline{B} + \delta B \end{aligned} \qquad \text{Eq. 3}$$

where the overbar signifies the mean expected (modeled) value, and the δ term corresponds to the unknown error. If we replace each deterministic term in Equation 2 with its probabilistic equivalent, separate out the first order error terms, and square them, we get the governing equations for both mean and variance propagation. The equation for storage from the above becomes

$$\overline{V}(t+1)+\delta V(t+1)=\overline{V}(t)+\delta V(t)+\left[\overline{I}(t+1)+\delta I(t+1)+\overline{H}(t+1)+\delta H(t+1)\right]\Delta t - \left[\overline{Q}(t+1)+\delta Q(t+1)+\overline{E}(t+1)+\overline{B}(t+1)+\delta B(t+1)\right]\Delta t$$

Eq. 4

Separating out the error terms,

$$\delta V(t+1)=\delta V(t)+\Delta t\left[\delta I(t+1)+\delta H(t+1)-\delta Q(t+1)-\delta E(t+1)-\delta B(t+1)\right] \quad \text{Eq. 5}$$

and squaring them yields the governing equation for storage variance:

$$\begin{aligned}\sigma^2_{V_{(t+1)}} &= \sigma^2_{V_{(t)}}+\Delta t^2\left[\sigma^2_{I_{(t+1)}}+\sigma^2_{Q_{(t+1)}}+\sigma^2_{H_{(t+1)}}+\sigma^2_{E_{(t+1)}}+\sigma^2_{B_{(t+1)}}\right]+\\ &2\Delta t^t\left[-\sigma_{Q_{(t+1)}I_{(t+1)}}-\sigma_{Q_{(t+1)}H_{(t+1)}}+\sigma_{Q_{(t+1)}E_{(t+1)}}+\sigma_{Q_{(t+1)}B_{(t+1)}}+\sigma_{E_{(t+1)}B_{(t+1)}}\right]+\\ &2\Delta t^2\left[\sigma_{H_{(t+1)}I_{(t+1)}}-\sigma_{E_{(t+1)}H_{(t+1)}}-\sigma_{B_{(t+1)}H_{(t+1)}}-\sigma_{B_{(t+1)}I_{(t+1)}}-\sigma_{E_{(t+1)}I_{(t+1)}}\right]+\\ &2\Delta t^2\left[\sigma_{I_{(t+1)}V_{(t+1)}}-\sigma_{Q_{(t+1)}V_{(t+1)}}+\sigma_{H_{(t+1)}V_{(t+1)}}-\sigma_{E_{(t+1)}V_{(t+1)}}-\sigma_{B_{(t+1)}V_{(t+1)}}\right]\end{aligned} \quad \text{Eq. 6}$$

Governing equations for other dependent variables are developed following the same procedure.

RiverWare Implementation

There are relatively few examples of uncertainty or risk evaluation computations in object-oriented modeling systems. Work can be found in the arenas of object-oriented database systems (see for example, De Caluwe, 1997), Agent Based Modeling (Bunt et al., 1998), and Bayesian networks (e.g., Koller and Pfeffer, 1997). In the water resources field, and in simulation modeling in general, there have been few attempts to integrate uncertainty analysis with an object- oriented structure. Reichert (1995) develops a “compartmentalized” modeling tool (AQUASIM), which divides aquatic systems into discrete functional pieces, such as biofilm reactors, stratified water bodies, soil columns, and river sections. AQUASIM provides for a simple error propagation of linear, uncorrelated, standard deviation values. Arnold et al., (1989) use an object oriented Intelligent GIS to model surface water systems. They use fuzzy set theory and related pattern recognition tools to classify features from various data sources, but do not use these “uncertainties” in simulation processes.

RiverWare is an object-oriented river basin modeling system developed by the Center for Advanced Decision Support for Water and Environmental Systems (CADSWES), at the University of Colorado. The system allows for short- or long-term basin planning including diversion, hydropower, water quality, reach routing, rule-based simulation and optimization capabilities.

One of the great benefits of RiverWare (and of object-oriented modeling in general) is the ability to compartmentalize functionality. In RiverWare, river and reservoir systems are represented as a network of objects. These software objects correspond to river reaches, reservoirs, diversions, canals, etc. The uncertainty algorithms developed in the previous section have been implemented into the “reservoir” objects within RiverWare. There are some very significant benefits which we can realize through this approach. These include:

- The ability to implement uncertainty computations on specific basin objects. Because RiverWare enables users to choose specific methods on individual objects, it can compute uncertainty on a subset of a larger model without significant modifications.
- Unlike Monte Carlo type simulations, the uncertainty analysis can be run directly in parallel with the simulation model. Thus, for example, if we are only concerned with quantifying uncertainty on a single reservoir in a large system (e.g., Colorado River Basin), the uncertainty computations run on that single object, while the "regular" simulation runs on all objects in the model. There is no need for repeated simulations (ala Monte Carlo) in order to develop distribution functions of results.
- The benefits of compartmentalization of functionality is also realized within individual objects. RiverWare users may choose from a number of different "methods" within several categories, on each reservoir in the model. The categories represent different physical processes which occur on the reservoir. Thus, there are categories for computing such things as evaporation, power generation, local gain/loss, generator capacity, spill, etc. Within each of these method categories, the user can select among various computational schemes. For example, evaporation may be computed using pan coefficients, atmospheric heat budget, user input, etc. The option also exists to not compute evaporation at all. Similarly, we can use compartmentalization to limit the computation of uncertainty to include only those variables that we have an interest in.

Case Study: Lake Mohave, Colorado River Basin

Lake Mohave is reservoir created by Davis Dam on the Colorado River, straddling the California-Arizona border just downstream of Hoover Dam. It's primary purpose is to re-regulate releases from the Hoover Dam powerplant, which is operated as a peaking-power facility. When Lake Mohave was created in the 1940s, it entrapped a population of native razorback sucker. The razorback sucker, once an abundant species in the Colorado River, is now endangered. Large mainstem reservoirs, resulting in dramatically colder river water temperatures, have decimated much of their habitat. The operating guidelines for Mohave outline rules for managing pool elevations during critical razorback sucker spawning and rearing seasons. These guidelines specify that:

- The pool elevation of Mohave should not drop more than two feet over any 10 day period from February 1 through April 30.
- The pool elevation should remain above 640 feet msl from April through the end of July.
- The pool elevation should remain above 637 feet msl until after September 16.

There are two significant sources of uncertainty in the current operational setting in which Lake Mohave releases are managed. First, there is no systematic modeling or prediction of local hydrologic gains (or losses) which impact reservoir storage. In existing models, evaporation, bank storage, hydrologic inflows, and precipitation are accounted for using a single lumped gain/loss term, which has traditionally been back-calculated from observed inflow, outflow and pool elevation values. The second source of uncertainty arises from a lack of precise day-to-day forecasting of releases from Hoover Dam which is the source of inflows to Lake Mohave. Long-term (monthly to annual) release targets for Hoover Dam are based on delivery obligations to water users in Arizona and California, and to Mexico. Within these fixed long-term release schedules, which are overseen by the Bureau of Reclamation (BOR), there is considerable leeway for short-term fluctuations (hourly to weekly). Western Area Power Administration (WAPA) is responsible for determining these short-term releases, based primarily on forecast demands for hydroelectricity. Hoover Dam powerplant is operated primarily as a peaking-power facility. As a hydroelectric system, it is very efficient at providing power on short notice for short periods. Operationally, WAPA provides BOR with a forecast of estimated releases (daily averages) up to six weeks into the future. This allows the BOR to plan reregulation from Mohave accordingly. Unfortunately, these predictions often are significantly different from the actual releases. The impact on mitigating pool elevation fluctuations for the razorback sucker are obvious; the larger the error in WAPA's predictions, the smaller the margin for error in taking corrective measures by modifying Mohave's releases. Further complicating the problem is that Mohave's releases themselves are subject to requests made by downstream diverters, and any excess undiverted water is essentially "lost" out of the system.

The goal of this study is to examine how these two sources of uncertainty affect the ability to forecast and manage Lake Mohave such that the guidelines of the biological opinion are satisfied.

We use historical forecast and observed data for hydrologic inflows and Hoover releases to generate variance values for inflow and hydrologic inflow parameters. Given covariances, we are able to make some quantitative statement about the magnitude of the uncertainties relative to each other, and to provide some measure of the impact of forecast errors on the ability of the BOR to meet its obligations for the Razorback Sucker Recovery Program.

Methods and Results

Forecasts of reservoir releases, storage, and diversions are made daily for the entire Lower Colorado River. These forecasts are for daily averages (flow) and end of day states (storage and pool elevation). For this work, we develop variance values for Mead, Havasu and Mohave reservoir releases by comparing the forecast and observed data records. Because the forecasts for the system are updated daily, we generate "day-ahead" error statistics for forecasts of 1 - 14 days ahead. Values for forecast uncertainty are given as the standard deviation of the forecast as a percent of the predicted value. Thus, for the period of record (January - May 1999), all of the 1 day ahead errors are compiled to generate a 1 day ahead variance estimate. This process is repeated for the historical record of forecasts of 2-14 days ahead. Uncertainty about local hydrologic inflows were initially suspected of contributing significantly to uncertain reservoir storage/pool elevation. Analysis of historical values of these hydrologic inflows showed that while there is significant variation, the magnitude of uncertainties from reservoir releases is an order of magnitude more influential.

Figure 1 shows the "days-ahead" forecast errors for releases from Mead (Hoover Dam), Mohave (Davis Dam) and Havasu (Parker Dam). As one would expect, the graph shows that in general, the farther ahead forecasts of releases are made, the larger the magnitude of the uncertainty. Note that there is an obvious correlation in the first week between the uncertainties of Davis' and Parker's outflows. This reflects the fact that Parker is a small, demand-driven reservoir, and any requests for water downstream are in essence passed upstream to Davis. Releases from Hoover Dam are significantly less predictable, and not statistically correlated, to releases from the downstream reservoirs. This increased uncertainty reflects the nature of the objective for which Hoover is operated, namely peaking hydropower. Unlike the lower reservoir releases, which are primarily used for municipal and irrigation delivery, Hoover's releases are subject to short-term spikes in power demand, resulting from a variety of uncontrollable factors such as weather patterns, changes in power availability, and economic fluctuations. "Days ahead" forecast errors for dam releases.

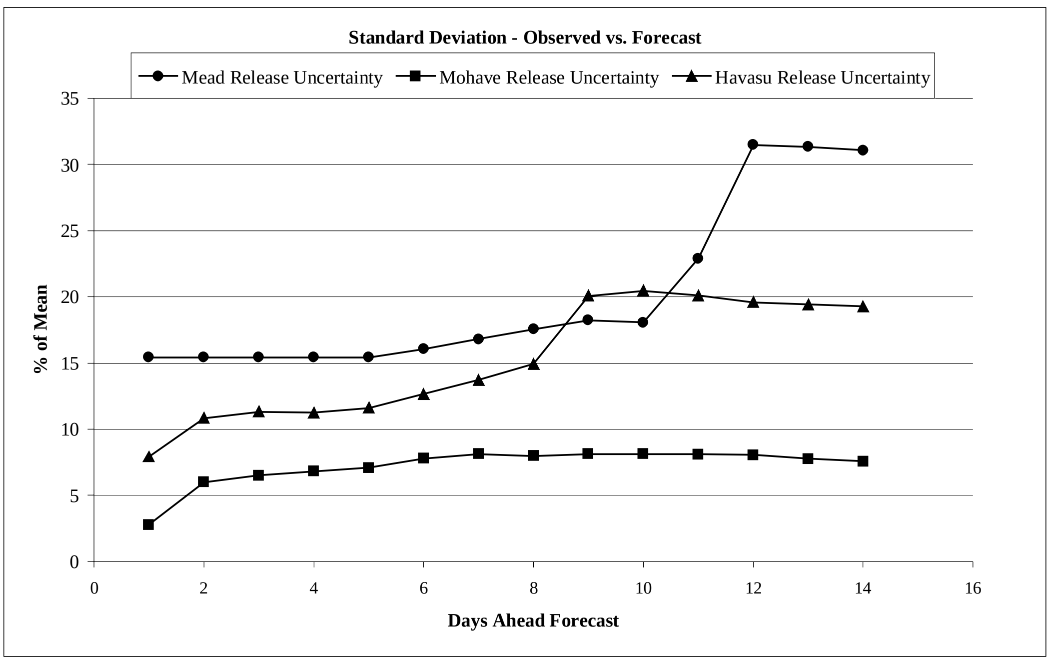

Figure 1. "Days ahead" forecast errors for dam releases.

The results of the study indicate that errors in the prediction of peaking power releases from Hoover Dam are significantly greater than those resulting from Mohave operations or unknown hydrologic inflows. Figures 2-5 show results of the simulation for four different scenarios. Figure 2 shows the 95% confidence interval around pool elevations on Mohave when uncertainty about local hydrologic inflows are taken into account. Similarly, Figure 3 shows the confidence bounds for uncertain outflows from Mohave, and Figure 4 shows the confidence bounds for uncertain inflows from Hoover. Figure 5 shows the cumulative effect of all three. Clearly, errors in release forecasts from Hoover, as shown in Figure 4, contribute the greatest percentage of error when predicting Mohave pool elevations.

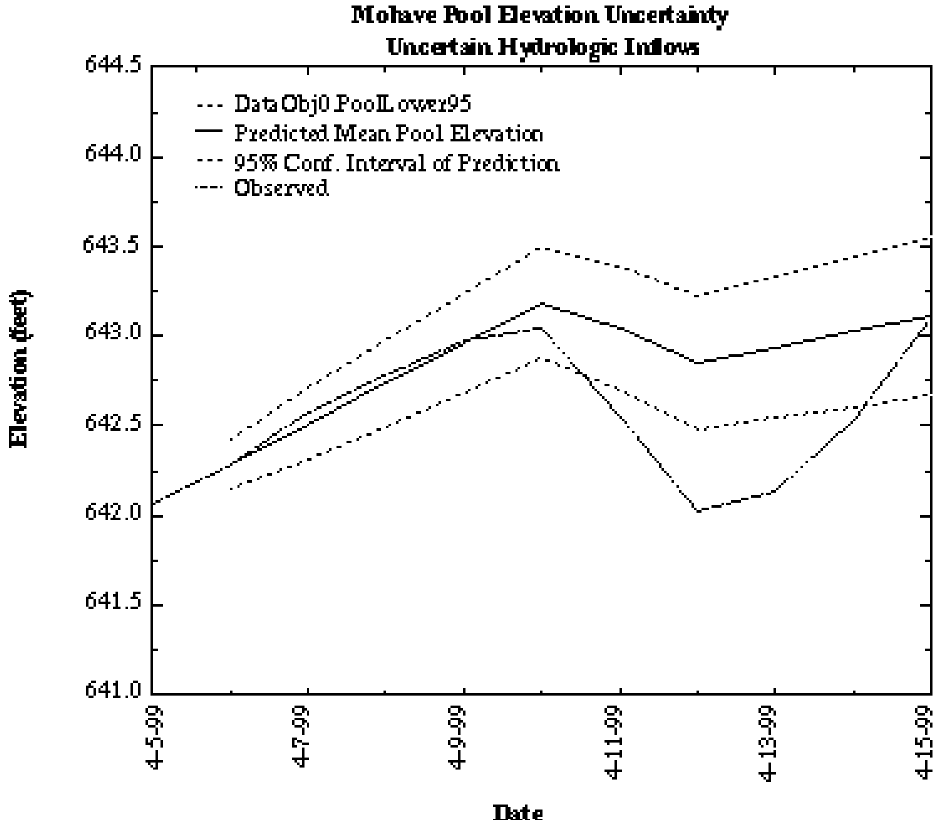

Figure 2. Confidence bounds on pool elevation based on hydrologic inflow errors.

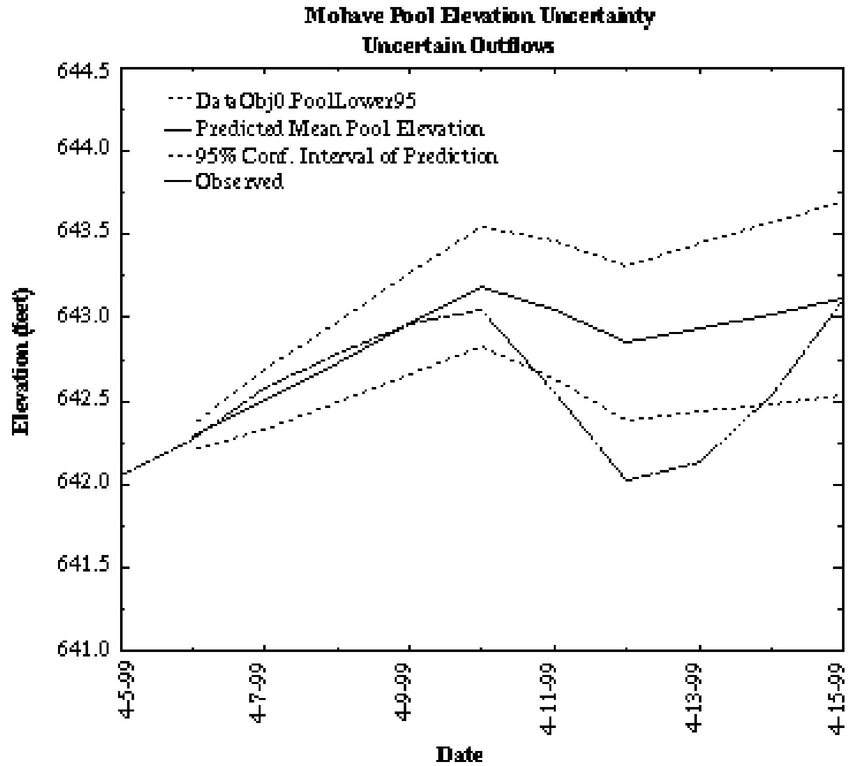

Figure 3. Confidence bounds on pool elevation based on outflow

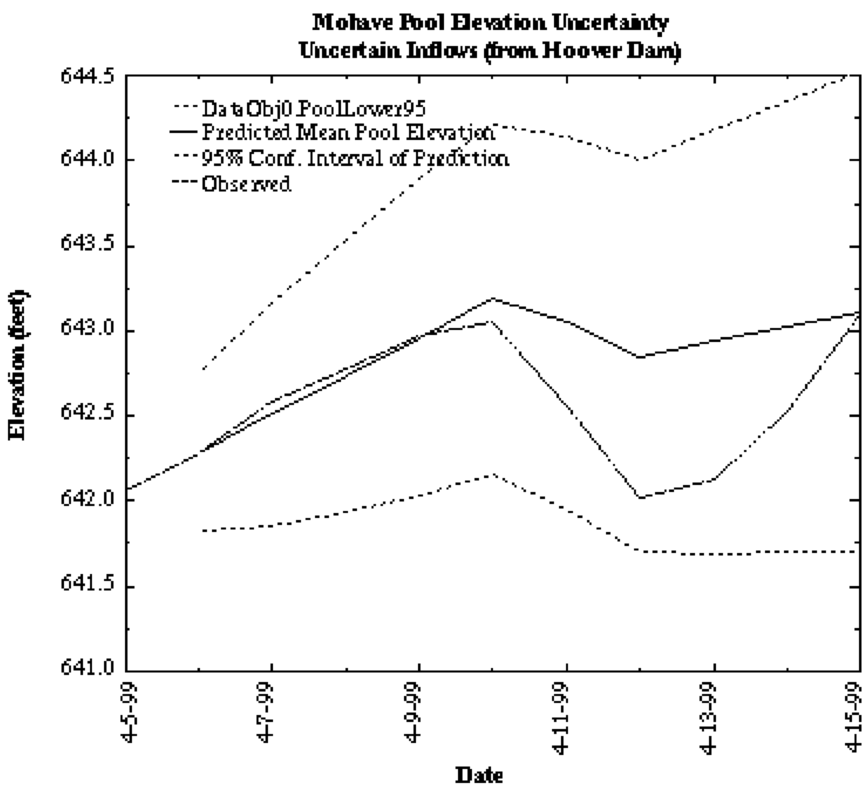

Figure 4. Confidence bounds on pool elevation based on inflow errors (release from Hoover Dam).

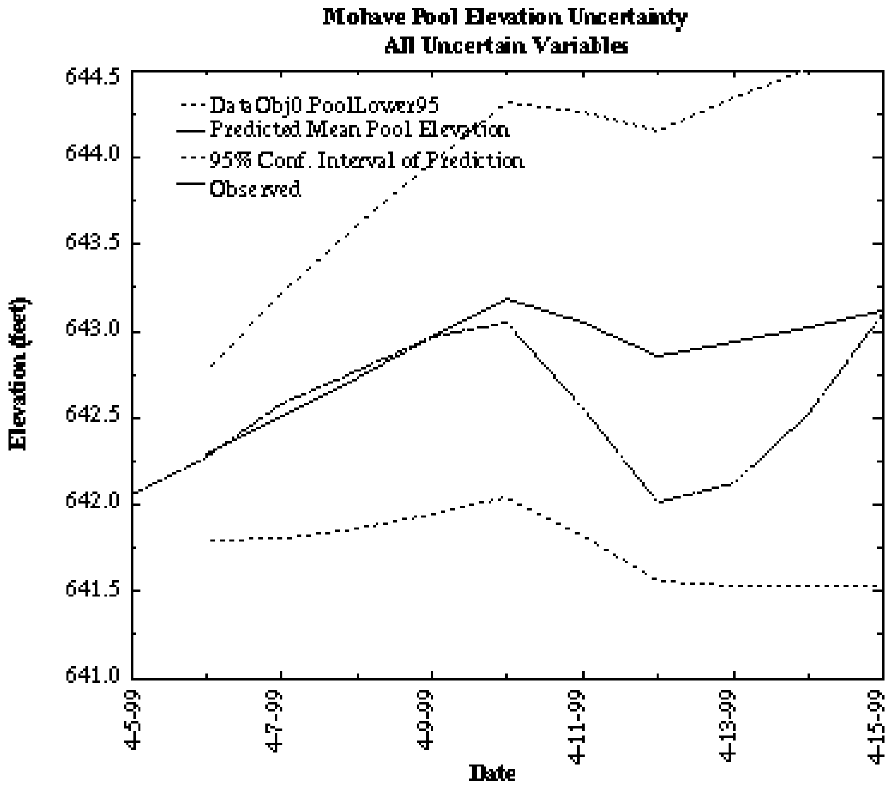

Figure 5. Confidence bounds on pool elevation based on sum of inflow, outflow and hydrologic inflow errors.

Conclusions

The FOSM method is a useful tool for identifying and modeling both physical and institutional uncertainties. In highly regulated systems, institutional uncertainties are often more important in terms of their impact on system predictability and control. Comparison of historical forecasts with observed data can provide managers with insight into operational policies which result in greater system uncertainty. Identifying these sources of uncertainty can guide managers in the development of future operational guidelines.

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