Theoretical error convergence of limited forecast horizon in optimal reservoir operating decisions

Gene Jiing-Yun You¹ and Cheng-Wei Yu¹

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[1] This study proposes a method of analyzing the error bound of optimal reservoir operation based on an inflow forecast with a limited horizon. This is a practical approach to real-world applications because current weather forecasts and climate predictions cannot necessarily achieve the “perfect forecast” required for optimal solutions. This study proposes a method to measure the error and error bound according to terminal stage boundary conditions, for which a theoretical convergence rate is derived. Our results suggest that convergence can be attained at a rate faster than the inverse of the extension of the study horizon. This demonstrates that the application of rolling horizons can improve the quality of decision making by exploiting available forecasts/information. When a perfect forecast is unavailable, the rolling decision procedure with regularly updated forecast information could help to avoid serious losses due to short-sighted policies.


1. Introduction

[2] An important consideration in hedging operations is how long hedging should be performed for particular operational frameworks. This problem is related to the question of how far into the future forecasting should be performed. In stochastic dynamic models of reservoir operations, decisions in the initial periods are not affected by forecast data beyond a certain point, which is known as the forecast horizon (FH), and the number of initial periods defines the decision horizon (DH) [You and Cai, 2008a]. In a previous study, we presented theoretical analysis applicable to determining the ideal FH for a given DH under the optimality condition of dynamic programming [You and Cai, 2008a]. However, from a practical viewpoint, two major concerns have to be addressed. The first is the assumption of a reliable probabilistic forecast of reservoir inflow. Current forecasting technology is unable to provide reliable hydrologic forecasts even for a few months, and a reliable long-range hydrological forecast is nearly impossible [Somerville, 1987]. Another concern is the sensitivity of information in the decision-making process. Operational policy in the current period may be affected by information in the distant future but is not necessarily sensitive to it [You and Cai, 2008a].

[3] A number of models with limited foresight have been applied to the operation of real-world systems. For example, the rolling-horizon model with limited foresight is a popular tool used in the analysis of dynamic operations, taking into consideration both operational efficiency and practicality [Chand et al., 2002]. As shown in Figure 1(a), implementing a rolling horizon begins with the establishment of a T1-horizon problem according to current conditions, such as initial storage and forecasted inflow, with release decisions made for the current period. The results of decisions made in period one are taken as the initial condition of period two (i.e., the ending storage of period one is the starting storage of period two). Observations and forecasts related to the system are updated up to period two, whereupon the model can be reformulated with an updated horizon T2, which is not necessarily equal to T1, as shown in Figure 1(b). This procedure is repeated with updated horizons from one period to the next. FHs that roll over periods are called rolling horizons or study horizons (SHs), representing a FH that is actually available for use in the analysis of any dynamic system [Bean et al., 1987].

[4] The rolling-horizon procedure is practical for reservoir operations, provided that weather forecasts and streamflow predictions are updated from one period to the next. Since December 1994, the Climate Prediction Center of the U.S. National Oceanic and Atmospheric Administration (NOAA) has been issuing forecasts of temperature and precipitation for the following three calendar months. The forecast is updated each month, and the 3 month window is shifted ahead month by month. Reservoir managers approve operational plans at the beginning of each period according to available forecast data. This process is usually performed on a weekly or monthly basis using rolling weather and hydrologic forecasts. A similar process was proposed by Shiau [2009], in which hedging for reservoir operations was performed for multiple periods in advance. In that study, hedging is rolled over each period and includes updated inflow information. As long as the forecasts are reliable, this kind of early hedging can be useful.
for the conservation of water for future use [Shiau and Lee, 2005; Shiau, 2009]. Nonetheless, selecting the length of the periods is crucial, inevitably involving a trade-off between the reliability of available information and the benefits of hedging. 

[5] Given these concerns, FHs based on the horizon theory are probably too distant to be of practical use [Chand et al., 2002]. A SH that is shorter than the ideal FH required by optimal decision making may lead to suboptimal decisions due to limited foresight. In this study, however, the authors took a realistic approach to current forecasting technology, in which the adoption of a myopic SH with an acceptable degree of error could be a useful exercise. In other words, it was assumed that distant information could be neglected, if a reasonable level of error were permissible. Thus, rather than trying to determine the ideal FH [You and Cai, 2008a], this study adopted a dual approach, determining how far the actual decision is from optimality using a limited but realistic foresight horizon. This is a more practical approach for real-world applications because current weather forecasts and climate predictions do not necessarily extend as far as the “perfect foresight” (FH), which would be required to obtain the optimal solution. 

[6] Decisions based on the rolling horizons are often suboptimal due to the current limitations of forecasting. This study defines error as the distance between solutions with a limited and the ideal forecast and attempts to identify a realistic FH with an acceptable level of error (i.e., error bound) by considering the trade-off among cost, data reliability, and decision accuracy. Lundin and Morton [1975] introduced the concept of error/error bound by defining the ε-optimality of a dynamic decision problem. Despite the wide acceptance of this concept, a common definition with illustrative details is still required. Morton’s [1981] first outline of the importance of applying the error bound concept was followed by other studies such as Kleindorfer and Kunreuther [1978] and Sethi and Sorger [1991]. Nonetheless, the error bound problem has yet to be studied systematically from a theoretical perspective, due to the complexity involved in developing a general analytical framework with which to evaluate rolling-horizon procedures [Sethi and Sorger, 1991]. Recently, Chand et al. [2002] revisited the error bound problem, which was proposed as a promising research topic deserving further attention. 

[7] Although the issue of error resulting from limited foresight is important to reservoir operations, relatively few studies have addressed this problem. Zhao et al. [2012] utilized numerical simulation to evaluate release decisions under a limited forecast. This study adopted a different analytical viewpoint to deal with a similar problem; the error bound of rolling-horizon optimality was analyzed for problems associated with reservoir operation based on the concept proposed by Lundin and Morton [1975]. The generality of such analysis can provide a more complete understanding of the problem. The authors have modified the original concept of horizon theory presented by You and Cai [2008a] and examined the properties of error bound to deal with problems associated with the dynamic operation of reservoirs. This study introduces a method of measuring error and error bound according to terminal stage boundary conditions. Under the assumption of an interior solution, the optimal strategy for operations will not lead to a situation in which the reservoir is empty or full. Thus, operations are affected by forecasting and can be improved by the extension of the FH [Morel-Seytoux, 1999; You and Cai, 2008a]. This enables the determination of a theoretical rate of convergence related to horizon extension for further application during operations.

2. Theoretical Rate of Convergence of Error with SH Extension

2.1. Formulation of the Optimization Problem

[8] In this paper, we considered the same problem formulation dealt with in You and Cai [2008a]. The reservoir operation problem was formulated as a dynamic optimization model with discrete multiperiods as well as a continuous state to facilitate a water supply reservoir. The economic value of a water supply is defined by the utility function of a composite user. For the nth time period, the utility is written as

\[ b_n = b_n(r_n, s_n), \]  

where \( b_n \) is a concave, monotonically increasing utility function, focusing on the use of water supply; \( r_n \) is the release of water, \( s_n \) is the reservoir storage at the beginning of the nth period, representing the state variable. The expected objective value that maximizes the utility over all time periods is written as

\[
\max_{\mathbf{r}} \left\{ B(\mathbf{r}, \alpha, N) = \text{EV} \left[ \sum_{n=1}^{N} \alpha^n b_n(r_n, s_n) \right] \right\},
\]

where \( n = 1, 2, \ldots, N \) is the index of time periods. \( N \) represents the length of the time horizon for the analysis of the problem, called the problem horizon. \( B(\mathbf{r}, \alpha, N) \) is the utility over all time periods. \( \text{EV}[\cdot] \) represents the expected value, \( \alpha \) is the discount factor, and \( \mathbf{r} = \{r_1, r_2, \ldots, r_N\} \) is the decision variable vector. There exists an optimal release vector \( \mathbf{r}^N_* \), which satisfies

\[
B(\mathbf{r}^N_*, \alpha, N) = \sup_{\mathbf{r}} B(\mathbf{r}, \alpha, N) = \text{EV} \left[ \sum_{n=1}^{N} \alpha^n b_n(r_n^*, s_n) \right].
\]
for a given initial storage $s_1$. Furthermore, for $T \leq N$, we define $r^{T_*}$ as the optimal release during period $[1, T]$ and define

$$B(r^{T_*}, \alpha, T|d) = \sup_{r \in \Omega} B(r, \alpha, T|d), \quad (4)$$

where $T|d$ represents the $T$-horizon with a given forecast $d$. Equation (4) provides the optimal solution for the $T$-horizon problem, with the optimal release decision ($r^{T_*}$) over the feasible domain of policy ($\Omega$) underlying a forecast of necessary information ($d$). A more detailed description of this formulation can be found in You and Cai [2008a].

2.2. Conditional Optimality

[9] Lundin and Morton [1975] defined $\epsilon$-optimality to represent the upper error bound of a suboptimal solution with a limited foresight horizon. The accuracy of the solution is described by a prescribed tolerance $\epsilon$. Studies were conducted to derive the error bound according to various definitions contingent on the intended purposes [Lee and Denardo, 1986; Denardo and Lee, 1991; Chen and Lee, 1995]. To address the error bound problem, the authors employed the same approach described in our previous study [You and Cai, 2008a]. Following Lundin and Morton’s definition, we extend the $\epsilon$-optimality condition as follows: A release policy $r^T_\epsilon(\epsilon, T, t|d)$ is conditionally optimal under a given threshold $\epsilon$, a SH $T \leq T_F$, a DH $t$, and a given forecast $d$; if for all $n \leq t$, $B(r^{T_*}, \alpha, t|d)$ $- B(r^{T_*}, \alpha, t|d) = \sum_{n=1}^{t} \delta_n \leq \epsilon$, irrespective of the periods beyond period $T$ (e.g., $T + 1, T + 2, \ldots$). When $\epsilon = 0$, $T$ is equal to the full FH $T_F$.

[10] The concept is illustrated in Figure 2. The upper part shows the path of decision variable $r$, and the lower part is the path of state variable $s$, for suboptimality with SH $T$ and optimality with FH $T_F$. The term $\sum_{n=1}^{t} \delta_n$ represents the sum of the error, which is the difference between the utility of the suboptimal policy $r^{T_*}$ and the optimal policy $r^{T_F}$, as shown in the hatched area in Figure 2. The parameter $\epsilon$ is the upper bound of the error. In the following, the error bound $\epsilon$ is further discussed in terms of reservoir operation problems.

[11] First, by replacing the problem horizon $N$ with the perfect FH $T_F$, equation (3) can be rewritten as

$$\max_{r^{T_F}} \left\{ B(r, \alpha, T_F) = \text{EV} \left[ \sum_{n=1}^{T_F} \alpha^n b_n(r_n, s_n) \right] \right\}. \quad (5)$$

[12] To determine the error bound $\epsilon$, we update the definition of optimal policy provided in equation (4). We convert a free-end dynamic problem into a fixed-end dynamic problem by introducing the end state variable $s_N$, expressed by equation (6) (similar to equation (4)).

$$\text{sup}_{r^{T_F}} B(r, \alpha, N) = B(r^{T_*}, \alpha, N) = \text{EV} \left[ \sum_{n=1}^{N} \alpha^n b_n(r_n^*, s_n^*) \right]. \quad (6)$$

Here $r^{T_*}$ represents the global optimal solution with given initial storage $s_1$, and ending state $s_N^*$, which is described in greater detail as follows.

[13] For a problem with SH $T$, the suboptimal decision is written as $r^{T_*}$. Given a DH $t$, the sum of the utility over the periods $[1, t]$ is written as $B(r^{T_*}, \alpha, t|d)$. If the value of $t$ falls within the range $t \leq T < T_F$, optimal decisions within the FH $T_F$ with a given forecast $d$ are represented as $r^{T_F}$. As such we can represent the total optimal utility with $T_F$.

Figure 2. The two boundary conditions (free-end and targeted storage) with a limited SH.
using two items: the utility within $T$ and the expected optimal utility between $T$ and $T_F$ as follows:
\[
\begin{aligned}
&\text{Max}_{r_t} \left\{ B(r, \alpha, T_F|d) = B \left( r^{T_*}, \alpha, T_F \right) \right\}_{(r_t=r^{T_*})} \\
&\quad + \text{Max} \left( \text{EV} \left\{ \sum_{n=T+1}^{T_F} \alpha^n b_n (r^{T_*}, s_{n-1}) \right\}_{(r_t=r^{T_*})} \right) 
\end{aligned}
\]
where $s_T(r = r^{T_*})$ means that the state (storage) at $T$ can be specified according to the optimal release policy derived under the perfect FH, which is set as the ending condition of the first part and the initial condition of the second part of the right-hand side of equation (7). Equation (7) divides the original free-end dynamic problem in equation (5) into two individual optimization problems, one with a fixed terminal state within the SH and the other is free during the period between $T$ and $T_F$, using $s_T(r = r^{T_*})$ as the initial condition of the problem. The state variable at $T$, $s_T(r = r^{T_*})$, conveys the information required for both problems. As shown in Figure 2, without solving the problem for the entire time horizon, an identical optimal policy $r^{T_*}$ can be calculated according to the boundary condition of the given correct terminal state. In this manner, we can simplify the $T_F$-period problem to a $T$-period problem with a given terminal state condition $s_T(r = r^{T_*})$.
\[
B \left( r^{T_*}, \alpha, T | d \right) = B(r^{T_*}, \alpha, T|d)_{(r_t=r^{T_*})}. 
\]
Compared to equation (7) which describes the optimal solution with the FH $T_F$, equation (8) describes the optimal solution with the SH $T$, if an appropriate ending condition $s_T(r = r^{T_*})$ is provided.

According to the law of continuity, storage monotonically decreases with release, leading to the property, in which both $B(r^{T_*}, \alpha, t | d)$ and $B(r^{T_*}, \alpha, T | d)$ are monotonically decreasing functions of $s_T$.

This describes the monotonically decreasing relationship between the decision vector and the terminal state. It can be intuitively explained as follows. If more water is stored for the future, beyond the SH, the utility within the SH will decrease. In accordance with this condition and equation (8), the error $B(r^{T_*}, \alpha, t | d) - B(r^{T_*}, \alpha, t | d)$ can be expressed as
\[
\begin{aligned}
B(r^{T_*}, \alpha, t | d) - B(r^{T_*}, \alpha, t | d)_{(r_t=r^{T_*})} &= \sum_{n=1}^{T_F} b_n, 
\end{aligned}
\]
where $b_n$ represents the error between the optimal utility within the DH $t$ underlying the SH $T$ and the FH $T_F$. Further, if we assume that the perfect FH is known, we can obtain the value of $s_T(r = r^{T_*})$.

### 2.3 Determining the Convergence Rate of the Suboptimal Solution

As expressed in equation (9), the presence of terminal state variable $s_T$ directly influences the error of decision with a limited SH. Therefore, the convergence rate of the suboptimal solution can be estimated by determining the finite change in utility over DH with respect to the terminal state variable $s_T$. This change in utility over DH $t$ is expressed as
\[
\frac{\text{d} B(r^{T_*}, \alpha, t | d)}{\text{d} s_T}.
\]
Equation (12) represents the mass conservation condition in this dynamic framework. The parameter $d s_T$ is the proportion of the terminal state variable contributed from period $n$ and is equal to the reduction in release policy $-d r^{T_*}$ multiplied by the residual ratio $(\partial s_T/\partial b_n)$ of storage. As discussed in our previous paper [You and Cai, 2008a], the residual ratio can be understood as the residual quantity of one unit of additional storage from each period when loss through delivery is considered.

The parameters $r^{T_*} + dr^{T_*}$ and $r^{T_*}$ are suboptimal policies with given boundary conditions and forecasts. In addition, we assume that both are interior optimal solutions. Hence, the marginal utility in each period with respect to the terminal state variable should be equal. A more detailed discussion can be found in You and Cai [2008b, 2008c]. The interior optimal condition can be expressed as
\[
\alpha \frac{\partial b_n (r^{T_*} + dr^{T_*})}{\partial s_T} = C_1
\]
\[
\alpha \frac{\partial b_n (r^{T_*})}{\partial s_T} = C_2.
\]
Subtracting equation (13) by equation (14) and expanding by $\frac{\partial T_n}{\partial T_n}$, 
\[
\alpha \frac{\partial b_n(r_{n}^{+}) + \partial T_n}{\partial T_n^2} - \frac{\partial b_n(r_n^{+})}{\partial T_n} = C_3. \tag{15}
\]
With the definition of equation (11), 
\[
b_n(r_n^{+}) - b_n(r_n^{+}) = \frac{\partial b_n(r_n^{+})}{\partial T_n}. \tag{16}
\]
We rewrite equation (15) as 
\[
\alpha \frac{\partial b_n(r_n^{+})}{\partial T_n} ds_{T_n} = C_3. \tag{17}
\]
With $ds_{T_n} = -\partial r_n^{+}/\partial T_n/s_n$ and $b_n'(r) = \partial^2 b(r)/\partial r^2$, we obtain 
\[
ds_{T_n} = \frac{C_3}{\alpha^2 b_n'(r_n^{+})} \left( \frac{\partial s_T}{\partial s_n} \right)^2. \tag{18}\]

[19] Combining equations (12) and (18) enables us to estimate the change in optimal policy with respect to $ds_{T_n}$, and the corresponding change of the utility in each period, $db_n'(r_n^{+})$, is estimated by the following two equations:
\[
ds_{T_n} = ds_T \frac{ds_{T_n}}{ds_T} = ds_T \sum_{n=1}^{T} \frac{1}{\alpha^2 b_n'(r_n^{+})} \left( \frac{\partial s_T}{\partial s_n} \right)^2 
= ds_T \frac{1}{\alpha^2 b_n'(r_n^{+})} \left( \frac{\partial s_T}{\partial s_n} \right)^2 
= ds_T \frac{1}{\alpha^2 b_n'(r_n^{+})} \sum_{n=1}^{T} \frac{1}{\alpha^2 b_n'(r_n^{+})} \left( \frac{\partial s_T}{\partial s_n} \right)^2. \tag{19}\]
\[
db_n'(r_n^{+}) = \frac{\partial b_n(r_n^{+})}{\partial T_n} ds_{T_n} = \frac{1}{\alpha^2 b_n'(r_n^{+})} \sum_{n=1}^{T} \frac{1}{\alpha^2 b_n'(r_n^{+})} \left( \frac{\partial s_T}{\partial s_n} \right)^2. \tag{20}\]
[20] The overall difference in utility within the DH can be expressed as 
\[
dB(t^{T+1_1}, \alpha, t|d) = ds_T \sum_{n=1}^{T} \frac{1}{\alpha^2 b_n'(r_n^{+})} \left( \frac{\partial s_T}{\partial s_n} \right)^2. \tag{21}\]

Similarly, the overall difference in utility within the DH with respect to the change in terminal state $T + 1$ with the extension of one additional period is as follows:
\[
\frac{dB(t^{T+1_1}, \alpha, t|d)}{ds_{T+1_1}} = \sum_{n=1}^{T} \frac{1}{\alpha^2 b_n'(r_n^{+})} \left( \frac{\partial s_{T+1_1}}{\partial s_n} \right)^2. \tag{22}\]

To make the derivation more meaningful, we introduce local risk aversion $\gamma_n() = -b_n'(r)/b_n()$ [Pratt, 2012]. In addition, $b_n'(r)$ is treated as a constant for the interior solution. Thus, equation (23) can be rewritten as
\[
\frac{dB(t^{T+1_1}, \alpha, t|d)/ds_{T+1_1}}{dB(t^{T+1_1}, \alpha, t|d)/ds_T} = \sum_{n=1}^{T} \frac{1}{\alpha^2 \gamma_n(r_n^{+})} \left( \frac{\partial s_{T+1_1}}{\partial s_n} \right)^2. \tag{24}\]

Equation (24) can be expressed in a more elegant and informative way as
\[
\frac{dB(t^{T+1_1}, \alpha, t|d)/ds_{T+1_1}}{dB(t^{T+1_1}, \alpha, t|d)/ds_T} = 1 - \Psi
\begin{align*}
\Psi & = \Phi_{T+1_1} - \sum_{n=1}^{T} \Phi_n \\
\Phi_n & = \frac{1}{\alpha^2 \gamma_n(r_n^{+})} \left( \frac{\partial s_{T+1_1}}{\partial s_n} \right)^2.
\end{align*} \tag{25}\]

2.4. Discussion

Equation (25) represents the theoretical convergence rate of error related to decisions in the optimal operation of the reservoir under the assumption of an interior solution. The parameter $\Psi$ can be recognized as the ratio of error reduction when the SH increases from $T$ to $T + 1$. According to observations, we determined that $\Psi$ is a function,
monotonically decreasing over time and lower bounded by zero. Taking a very simplified case without a time discount or constant risk aversion, the ratio of error reduction, $\Psi$, is close to $1/(1 + T)$. Consequently, when SH is relatively short, extending SH by an additional period could prove more effective in reducing error. For example, extending SH from 3 to 4 could reduce the error by more than $1/4 = 25\%$. However, with an increase in SH, the convergence rate is reduced. Similar findings were obtained through numerical simulation by Zhao et al. [2012]. They found that when SH is short, reservoir decisions are determined primarily by the length of SH. In this case, the extension of SH largely decreased the error bounds, which significantly improved the performance of the reservoir.

[23] When SH keeps extended, the length of the horizon is not the only dominant factor in error convergence. Time discount, risk aversion, and the capabilities of the reservoir also complicate its operations. Zhao et al. [2012] and You and Cai [2008a] also described this phenomena. However, complexity decreases when SH becomes relatively long. When $T$ is large, the denominator of $\Psi$ changes with $T$, such that the major influence is from its numerator $\Phi_{T+1}$.

[24] Zhao et al. [2012] concluded that when FH is long, the control factor associated with reservoir-related decisions is uncertainty in the forecast. Equation (25) confirms this statement, in which $\Phi_{T+1}$ becomes the variable with the greatest influence on the ratio of error reduction, $\Psi$. This issue was investigated more explicitly by You and Cai [2008a], who demonstrated that forecast uncertainty influences reservoir operations both in risk premium and aversion and in the ability of the reservoir to regulate inflow in the future. When considering the change in risk aversion over time, $\Phi_{T+1}$ actually decreases due to greater risk aversion in the distant future. A higher degree of uncertainty also increases the significance of the trend associated with increasing risk aversion. Error reduction would occur more rapidly in the beginning but would slow over time due to the influence of risk aversion. The capability of a reservoir to transfer water from period to period is represented by another factor $\frac{\partial \Psi}{\partial \Phi_{T+1}}$. This factor has less influence on the denominator of $\Psi$ than it does on the numerator. A smaller $\frac{\partial \Psi}{\partial \Phi_{T+1}}$ decreases the denominator of $\Psi$ resulting in a higher error reduction ratio. Less delivery capacity clearly leads to higher error reduction. A special case is $\frac{\partial \Psi}{\partial \Phi_{T+1}} = 0$; therefore, $\Psi$ equals zero. In this case, the assumption of an interior solution no longer holds. Optimality becomes static; error decreases to zero; and the reduction ratio simultaneously decreases to zero. Note that the assumption of an interior solution is not general and only consistently holds for very special dynamic problems. For reservoir operation problems, the bounded solution may occur when the solution touches a bound or constraint [Morel-Seytoux, 1999; You and Cai, 2008b]. The probability of reservoirs filling completely is influenced by physical limitations and plays a more important role under modest water stress levels [You and Cai, 2008a]. The error could be decreased more rapidly than the derived convergence rate once the upper or lower bounds are met. Differences in the capabilities associated with reservoir regulation result in different convergence rates. Smaller reservoirs have less capacity with which to regulate inflow, which can often lead to situations where the reservoir becomes completely empty or full. Under such circumstances, further forecasting would be moot because subsequent decisions would be unaffected by the forecast. Larger reservoirs permit the regulation of inflow over a longer time range; therefore, operations rely more on forecasting. The error decays less rapidly because larger reservoirs rarely reach their lower or upper bounds.

3. Conclusions

[25] This study determines theoretical convergence according to the proposed method of proceeding with decision making resulting from limited foresight, in which error diminishes at a rate faster than the inverse of the length of SH. Risk aversion and delivery capacity have a slight influence on convergence rate. The derivation shows that error decreases when the SH approaches the perfect FH, as determined by the horizon theory of You and Cai [2008a]. Before the FH is achieved, error rapidly approaches zero or a negligible level. The results of Zhao et al. [2012] and the authors’ previous study in numerical simulation of error bound confirm the theoretical derivation. Readers who are interested in the numerical results are referred to Zhao et al.’s [2012] paper and You [2008] dissertation.

[26] Compared to the results from the previous work [You and Cai, 2008a], with a limited SH, the distance to the FH is not proportional to the error. This is because the FH includes all information, even if it has only a slight influence on current policy. The theoretical derivation confirms the applicability of using rolling decision making for water resource systems. Our results demonstrate that error decays rapidly when the SH is suitably distant, which confirms the practicality of the rolling decision procedure. The error bound method can be used to estimate potential error. Knowledge of error and error bound is more useful for problems encountered in practical reservoir operations because perfect foresight is never available in the real world. Error bound can help to evaluate actual operations with limited forecasts. Understanding the potential of error convergence with respect to forecast availability in operations could enable reservoir managers to evaluate information more objectively and thereby improve the effectiveness of decision making.

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