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Improving Implicit Stochastic Reservoir Optimization Models with Long-Term Mean Inflow Forecast

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Abstract This technical note introduces a reservoir operation model based on implicit stochastic optimization (ISO) in which the release policy is guided by the forecast of the mean inflow for a given future horizon rather than by the prediction of the current-month inflow, such as in typical ISO models. The model also does not require the forecast of all inflows for the future horizon and shows to be more efficient in finding less vulnerable release policies when compared to several other explicit and implicit stochastic procedures.

Keywords Reservoir operation · Stochastic optimization · Long-term inflow forecast

1 Introduction

Implicit stochastic optimization (ISO) has been frequently applied to derive reservoir operating rules as an alternative to the classical stochastic dynamic programming methodology (SDP) (Celeste and Billib 2009; Celeste et al. 2009; Mehta and Jain 2009; Mousavi et al. 2005). ISO takes the uncertainties of reservoir inflows into account in an implicit way whereas SDP explicitly incorporates probabilistic inflow methods into the problem. ISO and other implicit stochastic techniques such as parameterization-simulation-optimization (PSO) (Rani and Moreira 2010; Celeste

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and Billib 2009; Koutsoyiannis and Economou 2003) are able to provide rule curves in an arguably simpler way than SDP and, as such, might be more attractive to operators who are skeptical to use sophisticated optimization approaches as a replacement to easier-to-understand simulation procedures.

In a recent paper (Celeste and Billib 2009), the authors have evaluated several ISO and PSO schemes and found that all of them performed better than SDP and provided release rules similar to the ones produced by perfect forecast optimization.

To develop the ISO-based release policies in the aforementioned paper, data of release, storage and inflow obtained from previous runs of a deterministic optimization model were grouped month-by-month and used to adjust regression-based curves, interpolation-based two-dimensional surfaces, and parameters of fuzzy rule-based systems. To decide the reservoir release at a given month, each of these three different ISO models only needed to know the initial reservoir storage together with the inflow predicted for the month, which is usual in reservoir ISO models. As pointed out by Shih and ReVelle (1994), the use of storage augmented by the expected inflow may bring more reasonable behavior as compared to using only the storage information in order to decide whether hedging (release reduction) should be triggered.

Among all ISO, PSO and SDP models applied by Celeste and Billib (2009), the ISO model that interpolated “rule surfaces” to the data was found to provide the best policies. The authors recognize, however, that the fitted curves and surfaces in these models still cannot account for all the nonlinearities present in the data. This happens mainly because the current-month release is not only a function of the current inflow but also depends on the inflow pattern for the next months. This suggests that taking long-term inflow prediction into account may improve the performance of the ISO-derived rule curves.

The use of long-term inflow forecast has been already dealt with in previous studies. Because of forecast inaccuracy, Shiau and Lee (2005) have proposed to use the deciles of monthly inflows to substitute for future inflows and devised a procedure to determine the optimal forecast lead-time. You and Cai (2008) also presented theoretical and numerical analysis to determine the best forecast horizon, beyond which current decisions on releases are not affected by forecast.

This technical note outlines new developments in the research by Celeste and Billib (2009) by introducing an ISO model that uses the prediction of the long-term mean reservoir inflow rather than the current-month inflow forecast or the forecast of a sequence of future inflows. This model, named ISO-LTF (for long-term forecast), is compared to all previously used models and the results indicate superior performance even though the rule curves are fitted to the data by just using classical regression analysis.

2 ISO-LTF Model

Implicit stochastic optimization uses a deterministic optimization model to operate the reservoir under several equally likely inflow scenarios and then examines the resulting set of optimal operating data to develop the rule curves. The inflow scenarios may be selected from the historical data (when the series is long enough) but are usually obtained by means of synthetic streamflow generation models.

Table 1 Categories of the predicted mean inflow for the next H_{fcast} months

Category	k	Percentage of normal mean
Very low	1	0%–35% of normal mean
Low	2	36%–70% of normal mean
Normal	3	71%–105% of normal mean
High	4	106%–140% of normal mean
Very high	5	$\geq$ 141% of normal mean

For each inflow ensemble, a different operating policy is found. The set of all policies is then examined in order to construct the release rules. Typically, the data are grouped by month (January to December) and a correlation of reservoir release as a function of initial storage and current inflow is sought. Depending on the data scattering, the operating policy for the month may be a simple linear equation or a high-order polynomial, whose parameters are calibrated by regression techniques. When the correlation is highly nonlinear, however, the release rule is perhaps better described by a neural network or a fuzzy rule-based system. These types of ISO models were all tested by Celeste and Billib (2009).

The proposed ISO-LTF model works exactly like described above with the exception that the current-month inflow is replaced by the forecast of inflow for the next couple of months (forecast horizon). One potential problem with this approach, though, is that long-term inflow forecast is rarely accurate, especially in semiarid regions, where this study is applied. However, instead of including a prediction of the actual inflow values for the following few months (or season), one may simply use the forecast of the expected mean inflow for the period. For example, the forecast might inform if the mean inflow for the next season will be lower or higher than the historical average inflow for the same period.[1] In this way, the rule curves can be developed by grouping the data of releases conditioned on initial storage and expected mean inflow for the coming few months. Thus, for every month, there would be several curves each with a different category of forecast, e.g., a curve conditioning release to storage and low future inflow, another rule conditioning release to storage and high future inflow, etc.

In this preliminary study, the operating data of each month obtained by deterministic optimization are grouped into five categories. Each category correlates the monthly reservoir release with the reservoir storage in the beginning of the month and the predicted mean inflow for the next H_{fcast} months, where H_{fcast} is the forecast horizon. Such mean inflow must be in one of the five categories listed in Table 1.

With the data clustered into categories, the model applies regression analysis to fit the following nonlinear equation to the data:

$$R(t) = d_k(\tau) \left[\frac{S(t-1) - S_{\text{dead}}}{S_{\max} - S_{\text{dead}}} \right]^{m_k(\tau)} \tag{1}$$

[1]Note that the use of mean inflow will not increase the accuracy of the forecast but its value will be arguably easier to estimate. It should be less problematic to estimate a single value than a good sequence of inflow values.

in which $R(t)$ is the reservoir release in month t; $S(t-1)$ is the reservoir storage at the beginning of month t; S_{dead} and S_{max} are, respectively, the dead storage and the storage capacity of the reservoir; and $d_k(\tau) \geq 0$ and $m_k(\tau) \in [0, 1]$ are the regression parameters, fitted to each category k ($k = 1, 2, \ldots, 5$) and each month of the year τ ($\tau = 1, 2, \ldots, 12$). Note that the index $t = 1, 2, \ldots, N$ is different from τ since t varies along the operating horizon of N months. The month of the year τ corresponding to t is calculated by $\tau = \text{rem}\left(\frac{t}{12}\right)$, which has the meaning that t is divided by 12 and the remainder is taken as the value for τ. If $\text{rem}\left(\frac{t}{12}\right) = 0$, then $\tau = 12$.

Thus, to determine the release $R(t)$ of a given month t, the mean inflow in the next H_{fcast} months is first predicted, then the category k to which it belongs is verified, and finally $R(t)$ is calculated by means of the above equation using the parameters $d_k(\tau)$ and $m_k(\tau)$ corresponding to category k and month τ.

3 Brief Description of the Models used for Comparison

The deterministic optimization model used by the ISO algorithm to operate the reservoir under the several inflow realizations is the one described by Celeste and Billib (2009) which uses the solution procedure refined by Celeste and Billib (2010). The objective function is the sum of squared deviations between releases and demands and the constraints are the reservoir continuity equation together with lower and upper bounds for storages, releases and spills. Evaporation losses are also taken into account.

The ISO, PSO and SDP models used by Celeste and Billib (2009) are briefly described below for convenience:

ISO-REG Model: The data resulting from the deterministic optimization is grouped conditioning release, $R(t)$, as a function of initial storage, $S(t-1)$, and current-month inflow, $I(t)$, and non-linear regression is applied to fit the following nonlinear equation (hyperbola) to the data:

$$R(t) = \frac{D(t)\sqrt{\left[S(t-1) - S_{\text{dead}}\right]^2 + I(t)^2}}{m(\tau) + \sqrt{\left[S(t-1) - S_{\text{dead}}\right]^2 + I(t)^2}} \qquad (2)$$

where $m(\tau)$ ($\tau = 1, 2, \ldots, 12$) are the parameters to be calibrated. The two-dimensional domain $S \times I$ is also divided into three regions and the data corresponding to each region are fitted independently. These regions are delimited by two lines having slopes of 30° and 60° from the axis of I.

ISO-SURF Model: Instead of fitting an equation, this model interpolates a two-dimensional surface of the form $z(x, y)$ to the data, where z, x and y represent release, initial storage and current-month inflow, respectively.

ISO-ANFIS Model: Uses the so-called adaptive neuro-fuzzy inference system (ANFIS) (Jang 1993) in order to develop a set of "IF-THEN" operating rules of the form IF $S(t-1)$ is A AND $I(t)$ is B THEN $R(t) = f(S(t-1), I(t))$, where

A and B are linguistic values defined by fuzzy sets and f is a function of the inputs.

PSO-HDG Model: PSO models first predefine a shape for the rule curve based on some parameters and then apply heuristic strategies to look for the combination of parameters that provides the best reservoir operating performance under possible inflow scenarios. The PSO-HDG model calibrates hedging parameters applied to the well-known standard operating policy (SOP). The SOP produces the simplest reservoir operating rule that prioritizes immediate water release up to the target demand (Draper and Lund 2004). The objective function of all PSO models is the same as used by the ISO models.

PSO-ZON Model: Divides the reservoir into six parameterized zones. Depending on the zone at which the initial storage level is located, a different fraction of the demand is released. The zone levels and the demand fractions are the parameters of the model.

PSO-2dHDG Model: Uses a rule that establishes a two-dimensional correlation of release, initial storage and current inflow so that hedging is applied only when a combination of active storage, $S(t-1) - S_{\text{dead}}$, and inflow is below a given parameter.

SDP Model: The recursive function F of the employed stochastic dynamic programming model is:

$$F_t^n\left(S(t-1), I(t)\right) = \underset{\text{feasible } S(t)}{\text{minimize}} \left[Z(t) + \sum_{I(t+1)} P_{I(t+1)} F_{t+1}^{n-1}\left(S(t), I(t+1)\right) \right] \quad (3)$$

where t is the current month and n is the total number of remaining months. Initial storage, $S(t-1)$, and current inflow, $I(t)$, are the state variables, while final storage, $S(t)$, is the decision variable. $Z(t)$ is the sum of squared deviations between releases and demands over all months from now on into the future and $P_{I(t+1)}$ is the unconditional inflow transition probability (no correlation between consecutive inflows).

4 Application of the ISO-LTF Model

The ISO-LTF model was applied to operate the Epitácio Pessoa reservoir (412 hm^3) located in the state of Paraíba, a semiarid region of Northeastern Brazil. Twenty ensembles of 26-year monthly inflow series were synthetically generated in order to calibrate the model. During the calibration, after operating the reservoir under each inflow scenario via deterministic optimization (with an operating horizon of $N = 26 \times 12 = 312$ months), the first and last three years of data were rejected to avoid the influence of starting and ending reservoir storages. Thus, only the resulting 20 years of data were used to fit the rule curves. The water demand assumed was the reservoir yield at 85% reliability (Celeste and Billib 2009).

The ISO-LTF model was used with H_{fcast} values of 0, 6, 12 and 36 months. For $H_{\mathrm{fcast}} = 0$, each monthly curve was adjusted to all data, with no division into categories. In this case, the inflow is the value expected for the current month (i.e., the value of inflow is known and equal to the forecast for the current month), just like in typical ISO models that do not consider long-term forecast. Due to space limitations, only the parameters calibrated for $H_{\mathrm{fcast}} = 12$ are presented here (Table 2).

After calibration, the ISO-LTF release rules were applied to operate the reservoir under 20 validation scenarios of monthly inflows (named valid-1, valid-2 up to valid-20), different from the calibration series. It must be mentioned that, during the these operations, the forecast of the mean inflow for the next H_{fcast} months was based on their real values, i.e., perfect forecasts.

The validation scenarios were also individually used as perfect forecast inputs to the deterministic optimization model and the operating policies obtained were taken as benchmark.

Taking N as the operating horizon (size of each series), a vulnerability index equal to

$$Vul = \frac{1}{N}\sum_{t=1}^{N}\left[\frac{R(t) - D(t)}{D(t)}\right]^2 \tag{4}$$

was applied to compare the performance of the ISO-LTF model against all models listed in Section 3 (see Table 3). Since no model gave the best results for each and every scenario, the same ranking approach used by Celeste and Billib (2009) was applied. This approach provides highest points to the model whose vulnerability is closest to the one found by perfect forecast optimization. The final ranking (1 = best) is shown in the last row of Table 3.

The operations under the SOP caused several short-time failure periods with high vulnerabilities.[2] The perfect forecast optimization model applied hedging prior to these shortage periods in order to mitigate the potential high deficits. All ISO (including the ISO-LTF) and PSO models allocated water in a similar way. Without applying the ISO-LTF model, Celeste and Billib (2009) found that the ISO-SURF and the PSO-2dHDG were the best models overall. Now, Table 3 shows that the ISO-LTF model with H_{fcast} values of 36, 12 and 6 yields (in this order) even better performance. The more the forecast is accurate, the better the operation becomes. It must be remembered that the forecast is only for the mean inflow value for the next H_{fcast} months and not all 36, 12 or 6 values of future monthly inflows. It must be also noted that the ISO-LTF model assumes that the forecast information is accurate. If it is not, the ISO model as well as any other model using that information would give inappropriate results. Thirty six months may be too long for practical meteorological forecasts. The results for $H_{\mathrm{fcast}} = 36$ is included to show that, in the uncommon case of accurate forecast estimates for such a horizon, one might get better reservoir operating rules.

[2]This was already expected since the SOP maximizes the *reliability* (percentage of non-failure periods) at the expense of providing more *vulnerability* (magnitude of failures) (Hashimoto et al. 1982).

Table 2 Regression parameters fitted by model ISO-LTF for $H_{\text{fcast}} = 12$

Regression parameter	Month											
	1	2	3	4	5	6	7	8	9	10	11	12
a) Category $k = 1$												
$d\ (\times 10^6)$	6.0206	6.0628	6.0386	6.0463	6.0434	6.0208	6.0448	5.9946	5.9884	6.0048	6.0223	6.0406
m	0.2332	0.2281	0.2265	0.2602	0.2892	0.2850	0.2846	0.2729	0.2630	0.2559	0.2480	0.2411
b) Category $k = 2$												
$d\ (\times 10^6)$	5.9541	5.8830	5.7712	6.0010	5.9645	6.0454	5.8914	6.0447	6.0604	6.0714	6.0970	6.0778
m	0.1873	0.1816	0.1556	0.1758	0.2065	0.2509	0.2359	0.2511	0.2423	0.2324	0.2277	0.2109
c) Category $k = 3$												
$d\ (\times 10^6)$	5.8726	5.8341	6.1898	5.9401	6.1537	6.0268	6.0268	5.9449	5.9736	5.9845	5.9913	5.9878
m	0.1109	0.0961	0.1393	0.1239	0.1721	0.1749	0.1822	0.1676	0.1635	0.1567	0.1485	0.1380
d) Category $k = 4$												
$d\ (\times 10^6)$	6.3994	6.1989	6.1127	6.0081	6.0415	6.2756	6.1454	6.3990	6.4163	6.4213	6.4137	6.3826
m	0.1344	0.1098	0.0966	0.0877	0.1120	0.1674	0.1693	0.1861	0.1793	0.1699	0.1584	0.1439
e) Category $k = 5$												
$d\ (\times 10^6)$	6.3516	6.2893	6.1291	6.0730	6.3751	6.3666	6.4211	6.4298	6.4011	6.4101	6.4002	6.3651
m	0.0936	0.0753	0.0400	0.0261	0.1494	0.1611	0.1572	0.1515	0.1414	0.1328	0.1207	0.1044

Table 3 Vulnerabilities for all models and validation scenarios

				ISO models			PSO models			ISO-LTF model for selected H_{fcast}			
	Det. Opt.	SOP	SDP	REG	SURF	ANFIS	HDG	ZON	2dHDG	0	6	12	36
valid-1	0.1384	0.2925	0.2256	0.1953	0.1733	0.1733	0.1695	0.1733	0.1675	0.1839	0.1741	0.1685	0.1745
valid-2	0.0848	0.1594	0.1362	0.1263	0.1165	0.1170	0.1121	0.1178	0.1127	0.1247	0.1146	0.1075	0.1042
valid-3	0.0696	0.1351	0.0937	0.0784	0.0738	0.0747	0.0806	0.0791	0.0767	0.0787	0.0742	0.0764	0.0875
valid-4	0.0518	0.1324	0.1167	0.0835	0.0679	0.0787	0.0673	0.0704	0.0672	0.0721	0.0650	0.0647	0.0605
valid-5	0.0515	0.0956	0.0850	0.0729	0.0678	0.0712	0.0706	0.0714	0.0689	0.0741	0.0680	0.0656	0.0673
valid-6	0.0986	0.2145	0.1748	0.1527	0.1389	0.1390	0.1412	0.1443	0.1401	0.1471	0.1391	0.1322	0.1360
valid-7	0.2498	0.3550	0.3154	0.3077	0.2990	0.3014	0.3022	0.3001	0.2963	0.3082	0.3001	0.2960	0.2840
valid-8	0.0367	0.1174	0.0720	0.0518	0.0509	0.0517	0.0646	0.0640	0.0596	0.0514	0.0508	0.0529	0.0469
valid-9	0.1312	0.2249	0.1849	0.1638	0.1496	0.1558	0.1488	0.1513	0.1463	0.1577	0.1512	0.1478	0.1468
valid-10	0.0219	0.0809	0.0491	0.0377	0.0351	0.0355	0.0459	0.0448	0.0413	0.0354	0.0334	0.0324	0.0304
valid-11	0.0092	0.0467	0.0387	0.0237	0.0313	0.0338	0.0432	0.0401	0.0381	0.0315	0.0290	0.0266	0.0218
valid-12	0.0389	0.1104	0.0919	0.0674	0.0525	0.0599	0.0540	0.0566	0.0526	0.0570	0.0557	0.0566	0.0642
valid-13	0.0720	0.1991	0.1229	0.0985	0.0846	0.0905	0.0889	0.0929	0.0878	0.0892	0.0859	0.0860	0.0887
valid-14	0.0243	0.0670	0.0387	0.0253	0.0369	0.0434	0.0510	0.0485	0.0441	0.0361	0.0352	0.0332	0.0316
valid-15	0.0290	0.0836	0.0629	0.0468	0.0412	0.0412	0.0482	0.0483	0.0454	0.0462	0.0435	0.0432	0.0425
valid-16	0.0000	0.0000	0.0043	0.0043	0.0081	0.0083	0.0086	0.0136	0.0097	0.0088	0.0067	0.0053	0.0041
valid-17	0.0597	0.1636	0.1227	0.1043	0.0973	0.1040	0.0975	0.0991	0.0952	0.1043	0.0944	0.0898	0.0871
valid-18	0.0397	0.1014	0.0814	0.0648	0.0544	0.0545	0.0590	0.0545	0.0528	0.0595	0.0543	0.0579	0.0567
valid-19	0.0214	0.0693	0.0494	0.0311	0.0292	0.0304	0.0370	0.0373	0.0340	0.0294	0.0287	0.0270	0.0233
valid-20	0.0008	0.0125	0.0133	0.0097	0.0180	0.0194	0.0260	0.0237	0.0220	0.0182	0.0174	0.0167	0.0132
Rank		12	11	7	4	6	8	10	5	9	3	2	1

5 Conclusions

This paper proposed a reservoir operation model based on implicit stochastic optimization that used the long-term forecast of the mean inflow rather than the prediction of all monthly inflow values for a given future horizon. Based on this forecast and on the observed current storage, the reservoir release could be estimated by means of the rule-curves calibrated by the model. The ISO-LTF model was applied to operate a reservoir in semiarid Brazil and its release policy performed better than those from various other explicit and implicit stochastic models such as PSO, SDP and ISO-ANFIS. Refinement of this model may still be possible by using more sophisticated approaches to correlate release as a function of storage and forecasted inflow rather than simple regression analysis, as was the case here.

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