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ORIGINAL RESEARCH ARTICLE

Use of mathematical optimization to construct optimal reservoir operating rules—A case study of the Barna reservoir in Narmada Basin, India

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ABSTRACT

This paper explains the benefits of using mathematical optimization to construct high performance reservoir operating rules and the related water rationing (deficit sharing) policies. The principal idea of the proposed approach is to generate perfect solutions obtained from an LP-based optimization model with the assumed foreknowledge of inflows represented with historical natural flows that are matched in the model with the current or projected levels of water demands. Water demands may include a mix of on-stream (e.g., e-flow targets or hydro power) and off-stream demands (irrigation or industry). The paper demonstrates the benefits of the proposed methodology by developing and testing short term operating rules on the Barna reservoir in Narmada River Basin in India. It shows that it is possible to achieve simulated results that follow the proposed rules and differ by only 2.5% in terms of the mean annual deficits from the best possible performance obtained using mathematical optimization with full foreknowledge of inflows.

Keywords: mathematical optimization; reservoir operation; rule curves; water demand management

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1. Introduction

A large number of papers related to river basin management models has been published in the last three decades, with reservoir operation as the principal focal point of investigation. Previous comprehensive literature review papers such as those compiled originally by Wurbs[1] and Labadie[2]. Each of those papers included a review of more than 50 different models. More recent review papers such as the one from Rani and Moreira[3], provide an overview of more recent developments on a conceptual basis, such as the emergence of multi-objective and stochastic optimization procedures. Multi-objective optimization is often pursued by academics, while generating limited interest among practitioners, as there seems to be no clear guidelines on how reservoir operators could use the multitude of the resulting pareto-optimal solutions. The open-source models based on the development environments such as the Python programming language by Tomlinson et al.[4], may seem appealing to the researchers who are familiar with such tools, however most practitioners need user friendly tools that can be mastered with a minimum of learning effort, and without requiring any expertise in various programming languages.

Dobson et al.[5] outline the importance of multiple time step optimization (MTO) as a useful feature capable of developing valuable optimal reservoir operation for each simulated year. They also believe that such solutions provide good training data for machine learning algorithms (MLA). This claim has been investigated by Ilich and Basistha[6], who found that it is much better to make an informed guess about the incoming runoff using MLAs and solve the reservoir operation as an optimization problem that minimizes downstream flood damage or deficits in dry years, as opposed to trying to achieve the same by generating informed guesses of suitable reservoir outflows, which has been an on-going trend among researchers for in the last two decades, as attested for example by Koutsoyiannis and Economou[7]. A similar approach of "guessing the best outflows" was developed by Bhaskar and Withlach[8] using the results of mathematical optimization as input into regression models, where the target reservoir releases were estimated based on the current storage levels, inflows and water demands. These efforts were aimed to replace the rigid nature of the rule curves, a concept initially proposed by Revelle et al.[9] that is still the most common approach used in practice by reservoir operators. Other efforts to create operating rules by learning from perfect solutions obtained using optimization over lengthy input data series have been published in the past by Turgeon[10]. There is still no widespread agreement on how to deduce operating rules from these solutions. Rule curves have traditionally been developed by simulation models using the trial-and-error approach, ending in a fixed curve shape for all years. The fixed shape may work well in normal years where reservoirs are filled during the high flow seasons, but it creates problems when modeling back-to-back dry years where water rationing policies have to be combined with the development of time-dependent reservoir storage zones. A trial-and-error simulation approach for finding the best shape of these multiple zones and the best rationing policy becomes cumbersome, especially for systems with multiple reservoirs. This paper proposes a way to statistically analyze the MTO solutions that can provide a quick way to develop and test new operating rules that can be easy to understand and follow. Section 2 includes a description of the MTO solution concept; Section 3 provides an algorithm that develops the MTO solutions to develop reservoir operating zones and water rationing policies; Section 4 provides a numerical example of this algorithm using the data from an existing system in India, while Sections 5 and 6 provide conclusions and references.

2. Multiple time step optimization

River basin planning has traditionally been based on the use of long time series of runoff estimates, usually based on the reconstructed historical natural flow records, and the current or projected levels of water demands. The purpose of using computer models was to provide insight into the best system performance, which can be developed using advanced knowledge of inflows and the use of mathematical optimization. Although this approach has been known for some time, having been used in studies such as the one related to the creation of the California Water Management Plan as part of the CALVIN[11] project, it is still not widely accepted, owing primarily to the inertia of the practitioners who are used to using the simulation models. However, creation of short-term operating rules relies on the conjunctive use of multiple step optimization in combination with the deficit sharing constraint, which is rarely used among practitioners. Justification for this approach is simultaneous optimization of water supply and water use is demonstrated by Ilich et al.[12], especially as it pertains to irrigation, since irrigation is usually the largest water user. The approach is briefly outlined below.

Very few commercially available models such as the RiverWare as reported by Zagona et al.[13], OASIS[14] and WEB.BM[15] are capable of solving optimization for multiple time steps simultaneously, with the WEB.BM being the only one publicly available as a web application. The solution process is explained in **Figure 1**, where the dashed lines represent the carry over storage between three consecutive time steps, while the elements within each of the three rectangles represent an example of all river basin components for one time step. Initial storage at the start of the first time step is depicted with V_{ini}, while Q_t (t = 1, 3) represents inflow in time step t. Any finite number of time steps can be solved simultaneously using this approach. The optimization problem can be posed as maximization of benefits. The objective function is applicable for all time steps and for all stakeholders in a river basin, which explains the double summation over both time and space:

$$Obj.Function = Max \sum_{t=1}^{m} \sum_{i=1}^{n} Y_{i,t} P_i \qquad (1)$$

where the allocated flows are represented by $Y_{i,t}$, target water demands are $D_{i,t}$ ($Y_{i,t} \leq D_{i,t}$), while P_i represents the pricing vector that attaches the value of water to each water user i.

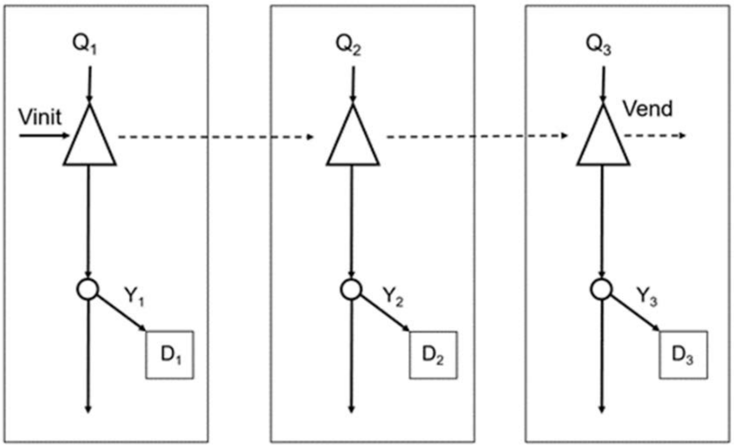

Figure 1. Multiple time step solution network for 3 consecutive time steps.

The constraints to optimization include the mass balance, maximum outflow from storage reservoirs (based on the storage spillway curve with assumed maximum opening), net evaporation on reservoirs (which are a function of storage that determines the water surface area), and a number of other constraints that may be related to existing system configuration, such as the constraints related to hydro power plant capacities or irrigation return flows. Additional constraints that ensure equal deficit sharing in time during dry years when deficits are inevitable ensure simultaneous derivation of the optimal reservoir rule curve as well as the optimal amount of demand hedging (water rationing), as depicted in **Figure 2**.

$$\frac{Y_t}{D_t} = \frac{Y_{t+1}}{D_{t+1}} \quad {}_{t=0,T} \qquad (2)$$

The above constraint prevents the model from premature emptying of storage during dry years, while simultaneously allocating minimal deficits evenly over the entire irrigation season[16,17]. This constraint ensures equal relative deficits for all time steps within an irrigation season, as shown in **Figure 2**. Without it, any other distribution of deficits throughout the season would seem equally optimal based on the objective function (1), while the actual differences in their output are drastic, which could often result in crop failure if large deficits persist for a month or longer.

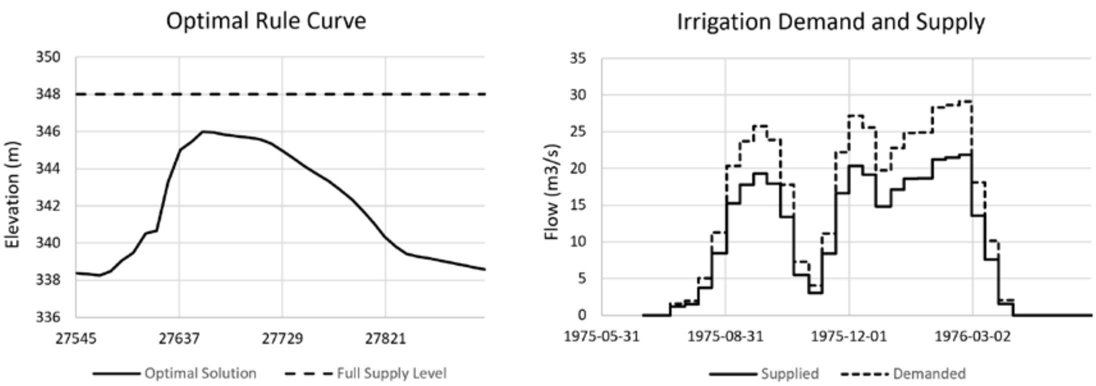

Figure 2. Simultaneous optimization of rule curve and demand hedging.

The optimal rule curve and its corresponding water supply pattern shown in **Figure 2** were obtained by conducting an optimization run over the entire hydrologic year with the constraints defined in Equation (2). As a result of having insufficient water supply, the model derived a reduction in water supply such that the deficits were evenly distributed throughout the entire year. Having the ability to provide optimal reservoir trajectory over the entire irrigation season along with the optimal level of water use for the given hydrological conditions for each simulated year forms the basis of developing an algorithm that can be used to quickly assess the reservoir operating rules for a typical range of hydrologic conditions.

The ultimate goal of using a comprehensive river basin model is to learn how to use the multiple time step optimal (MTO) solutions to create the reservoir operating zones and demand management policies. To define sound reservoir operating rules, we first need to define the concepts of irrigation failure, which is closely associated with the conditions that correspond to crop failure. Typically, a 10% deficit in supply will not cause crop failure. Irrigation failure is associated with sufficiently long cutoff in water supply that will result in the crop reaching the wilting point. Consequently, irrigators want to manage storage such that they minimize variations in supply from one 10-daily period to the next. Hence, for all practical intense are purposes, avoiding zero supply in any irrigation canal for any 10-daily period can be considered as the ultimate goal of sound reservoir operation. Irrigators' success should be determined in terms of the farmers' ability to simultaneously manage both the available storage and water demands. When farmers feel that the forthcoming irrigation season will be drier than usual, and these feelings are accompanied by observations of the available storage levels being significantly below expectations, they typically follow a policy of reducing the irrigated area, so as to safeguard successful crop yield with reduced water supply. The approach in this paper is aimed to propose a scientific method to determine water rationing policies at the beginning of an irrigation season, rather than relying on the gut feelings of the farmers, which is the current modus operandi.

Multiple time steps optimization is an approach that is well reviewed by Dobson et al.[5], where dynamic programming (DP), originally proposed by Bellman[18] is frequently cited as the solution engine. However, outside of academia, there are no well-known and widely used models among water resources practitioners that rely on dynamic programming. In addition to a recognized problem with dynamic programming known as "the curse of dimensionality", DP also has reduced accuracy compared to LP, since dynamic programming requires discretization of each decision variable into a finite number of defined states, one of which is then selected for the final solution by the DP algorithm, which affects the final accuracy of the solutions. Popular models that have achieved widespread use among practitioners such as MODSIM by Labadie et al.[19], WEAP by Yates[20], REALM by the State of Victoria[21] or RiverWare[13] all rely on the use of LP solvers. In addition to the above, it is not clear how dynamic programming would include the model constraint defined by Equation (2), while this implementation is relatively straight forward within the LP modelling framework.

Since the WEB.BM optimization model can determine the best possible combination of water supply and demand management, the success of the proposed short term operating rules resulting from this study should be determined in terms of the deviation of a simulated model solution from the solution developed using the MTO approach. The simulation follows simple storage and demand management rules. The closer the simulated solution comes to the MTO solution that is based on perfect foreknowledge of the hydrologic conditions, the higher the success of the proposed operating rules. The operating rules are based on knowing only the starting storage level and having water demand forecasts for a single time step, thus mimicking the operators' short-term decisions which are typically based on those two input data parameters.

3. Development of reservoir operating rules

While MTO solutions provide valuable insights into reservoir operation when inflows are known, there is no widely accepted methodology how to use these solutions to create reservoir operating rules that are easy to understand and follow. This paper investigates one possible approach of using MTO solutions for development of reservoir operating rules, with a note that this field is still an active area of research, especially in view of the fact that the MTO procedure can be used with stochastic hydrologic input for lengthy series of 1000 or more years of hypothetical inflows. The work presented here is easy to understand and replicate by the practitioners. It should be noted that the length of the hydrological input is important for the algorithm presented here. In general, the longer the input data series, the more reliable the results of the application. The numerical example presented in this paper relied on the use of 46 years historical natural flow series. The algorithm consists of the following steps shown in generic terms in the block diagram in **Figure 3**, and explained in more detail in the numerical example in Section 4.

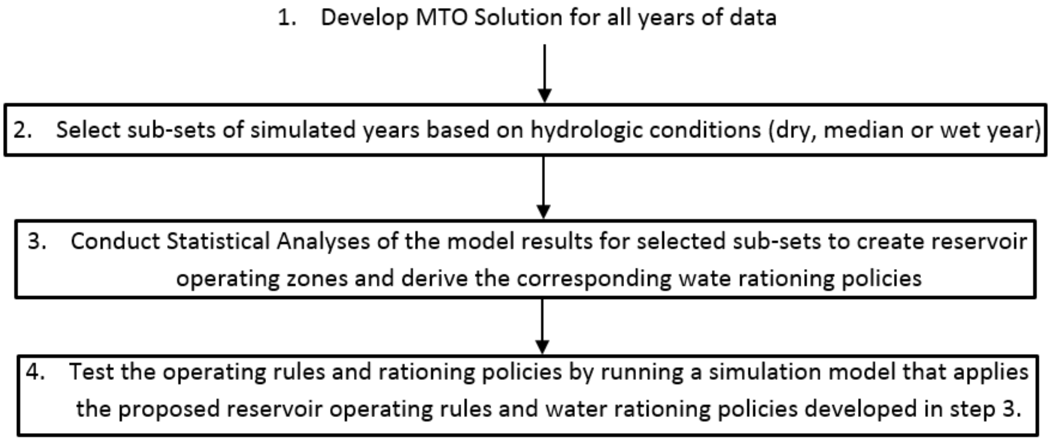

Figure 3. Algorithm for development of reservoir operating rules bas on MTO solutions.

There are several ways to conduct Step 2. This paper presents one approach based on sorting out the simulated years on the basis of the lowest storage level reached in each simulated year. This approach takes into account the total available water supply for each simulated years, which has two components—left over storage from the previous year and the runoff in the current year. Given the steady water demands assumed in each year, the lowest simulated water level reached in each year can be understood as a relevant statistic obtained from the MTO results that can rank all simulated years from the driest to the wettest. This enables selection of the representative sub-groups for dry, median and wet years. Step 3 involves the use of simple statistics applied on the selected model solutions that belong to the sub-groups defined in Step 2, which provided suggested operating zones and water rationing policies. Analyzing MTO solutions for the purpose of constructing reservoir operating rules is an active area of research, and the approach proposed in this paper is certainly not the only one. However, it does merit attention due to its simplicity and due to the quality of the results presented in the numerical example in Section 4.

4. Numerical example

Narmada River Basin is one of the major river basins in India. It is a westward flowing basin show in **Figure 4**, with over 28 billion m^3 of storage distributed among four large reservoirs and a number of smaller reservoirs. The Barna reservoir is a medium size reservoir with live storage of 540 million m^3.

Figure 4. Location of Narmada River Basin.

The Barna reservoir is located in the upper portion of Narmada Basin, draining its outflows into the Narmada River along with the Bargi and Tawa reservoirs as shown in **Figure 5**.

Figure 5. Location of Barna reservoir.

It should be noted that modelled irrigation demand was based on the average 10-daily withdrawals into the irrigation canal. As is usually the case this requirement covers domestic and stock water demand in addition to irrigation, and fills multiple smaller storage ponds on the village level, so the water demand pattern is similar from year to year. Historical inflows into the reservoir from 1972 onward were available from previous studies.

4.1. Initial MTO solution

In addition to the Barna irrigation demand, an all-time minimum e-flow target for downstream river channel of 2.5 m^3/s has been set up in the model. A perfect trajectory of reservoir levels resulting from the MTO optimization for all simulated years is provided in **Figure 6**.

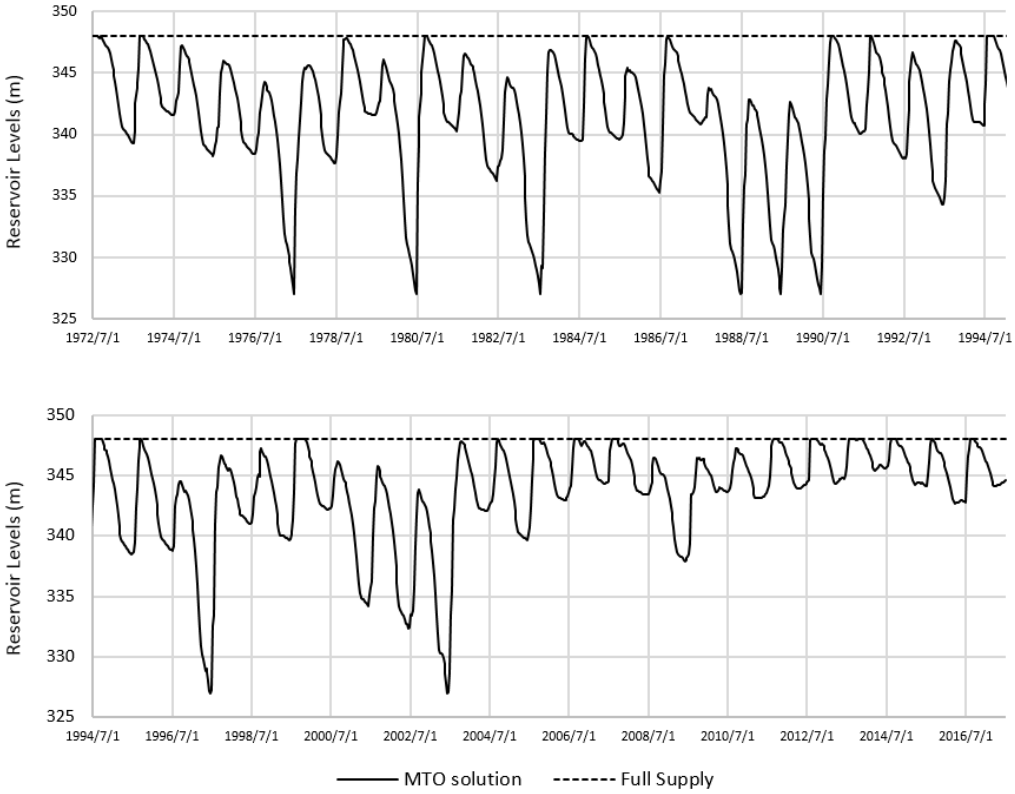

Figure 6. Barna reservoir levels obtained using MTO optimization.

We can distinguish 8 very dry years in which the storage has reached the dead storage zone of 327 m, and several dry years of medium severity with the lowest levels reaching 335 and 340 m. One interesting finding for all severely dry years is that they did not manage to refill the reservoir to the full supply level. Associated with each dry storage zone is the Barna irrigation performance, which will typically exhibit higher deficits in drier years, especially if the starting storage on 1 July was lower than usual. The same water demands were used in each year, indicating the average water demands that were provided historically in the most recent years as a representative of the current water demand levels.

4.2. Statistical analyses of the MTO solution

The storage levels and obtained from the MTO solutions were grouped based on the severity of deficits and the magnitude of drawdown required during the simulation. The driest years caused the highest deficits and the drawdown that typically reached the top of the dead storage zone. The three typical groups are identified by their overall annual deficits and the simulated years in the first two columns of **Table 1** below. The remaining columns in this table show the storage levels at the end of the 10-day periods in July and August. Only two months are presented here for brevity, while the model has produced the storage levels for all 36 periods of a 10-daily time step simulation.

Table 1. Storage levels from MTO solution for selected years.

Very dry years							
Deficit	**Year**	**10-July**	**20-July**	**31-July**	**10-August**	**20-August**	**31-August**
25.00%	1976	334.97	336.48	337.21	339.65	340.33	341.41
13.11%	1979	341.77	342.12	342.35	343.79	345.40	345.83
12.24%	1982	338.33	338.60	338.85	339.40	341.48	343.78
25.00%	1987	338.39	338.60	338.78	339.15	339.18	341.57
40.83%	1988	332.55	335.77	336.70	340.81	341.24	342.86

Table 1. (*Continued*).

Very dry years							
Deficit	**Year**	**10-July**	**20-July**	**31-July**	**10-August**	**20-August**	**31-August**
45.27%	1989	332.22	333.35	334.21	337.34	339.45	341.56
12.54%	1996	337.50	337.83	341.68	342.41	342.77	343.64
17.73%	2002	333.14	333.21	333.58	335.45	339.00	341.53
-	Average	336.11	336.99	337.92	339.75	341.10	342.77
-	Standard deviation	3.43	2.96	3.16	2.65	2.17	1.58
Moderately dry years							
	Year	**10-July**	**20-July**	**31-July**	**10-August**	**20-August**	**31-August**
25.00%	1975	337.21	337.74	339.04	339.20	342.26	344.18
5.00%	1977	336.79	337.90	339.67	341.11	342.62	344.31
5.00%	1981	340.93	342.38	342.82	344.61	345.97	346.14
5.00%	1985	339.39	339.64	340.66	342.76	344.60	345.29
0.00%	1992	338.09	338.40	340.49	342.01	344.33	346.12
15.00%	2000	341.90	342.79	344.28	345.03	345.35	345.76
15.00%	2001	335.27	339.32	341.90	342.54	344.53	345.56
0.00%	2008	343.72	344.09	344.37	345.80	346.49	346.52
-	Average	339.16	340.28	341.65	342.88	344.52	345.48
-	Standard deviation	2.86	2.46	2.03	2.19	1.49	0.85
Normal and wet years							
	Year	**10-July**	**20-July**	**31-July**	**10-August**	**20-August**	**31-August**
12%	1973	340.24	342.57	343.83	344.17	345.35	348.00
5%	1978	341.21	342.81	343.55	344.19	346.01	347.79
0%	1991	340.21	340.44	342.32	343.48	345.06	348.00
5%	1995	338.64	339.45	342.26	343.84	346.11	347.28
0%	2004	342.94	343.05	343.65	344.74	345.83	347.84
-	Average	340.65	341.66	343.12	344.08	345.67	347.78
-	Standard deviation	1.58	1.62	0.77	0.47	0.45	0.30

The statistical analyses of the selected sub-sets of the MTO solutions are limited to only the average and the standard deviation of the storage levels at the end of each 10-daily period. There is no widely accepted guideline on how these solutions should best be analyzed to provide guidelines for the development of the short-term operating rules. This topic remains open to future research. However, even at the most mundane level using the simplest statistics such as the average function, it is possible to obtain respectable results, based on the short-term operating rules which are represented by the operating zones in **Figure 7** that are based on the average storage values obtained from **Table 1** and the proposed water rationing policy, which is explained below.

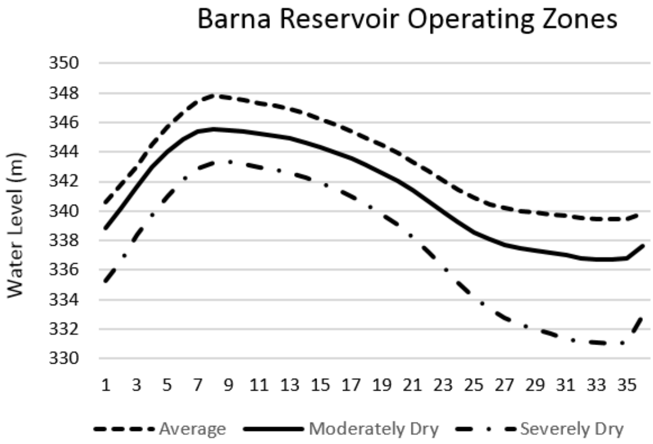

Figure 7. Barna reservoir operating zones.

The above zones define the following operating policy:

1) For water levels between 348 m and the Average (blue) line in the above graph, the model will provide 100% of target water demand;

2) For water levels below the Moderately Dry (red line) and the Average levels (blue line), reduce water demand to 80% of the ideal target;

3) For water levels between Moderately Dry (red line) and Severely Dry (green line), reduce water demand to 65% of the ideal target; and,

4) For water levels below Severely Dry (green line), reduce water demand to 50% of the ideal target.

The results of the above policy are presented in the next subsection.

4.3. Comparison of MTO solution with the solution obtained using the proposed operating rules

The proposed rules managed to generate a solution that is reasonably close to the solution obtained using the MTO procedure. Note that the differences in individual years are also caused by different storage levels at the start of the year in the two simulations. Different starting storage at the beginning of the dry season explain why some years such as 1973, 1995 and 1999 have higher deficits in the MTO run than in the rule-based simulation. On average, however, the rule-based simulation that follows the above deficit reduction policy in combination with reservoir operating zones provides a solution which is remarkably close to the MTO solution based on the assumed foreknowledge of inflows for the whole year ahead, yielding the average deficits of 9.75% over all simulated years, while the overall average of deficits in the MTO simulation was only 2.5% lower at 7.25%, as demonstrated in **Figure 8**. E-flow targets are also maintained in both simulations, with no failures to maintain 2.5 m^3/s at all in the MTO run, while the Rule-based simulation has only three weeks where water deliveries are slightly below 2.5 m^3/s. It is instructive to compare the storage levels from the MTO optimization solution and the solution based on the application of the zoning operating rules, which is shown in **Figure 9**.

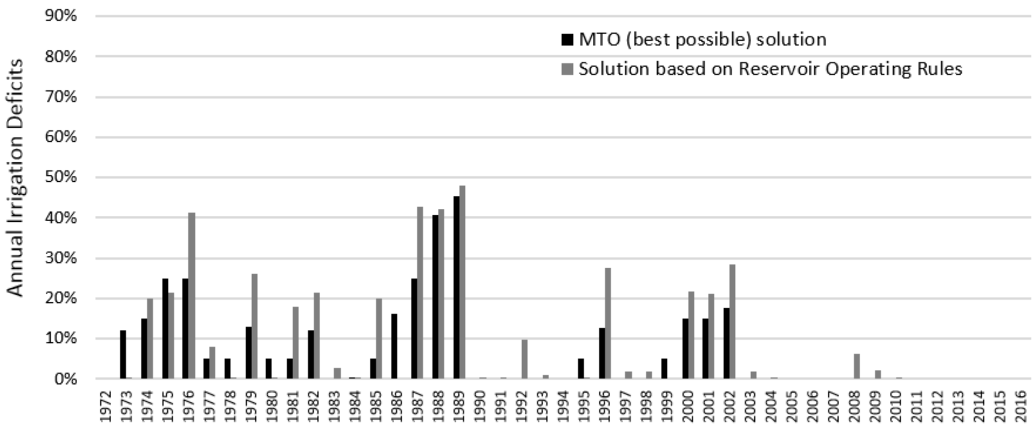

Figure 8. Comparison of annual irrigation deficits from the MTO solution and rule-based simulation.

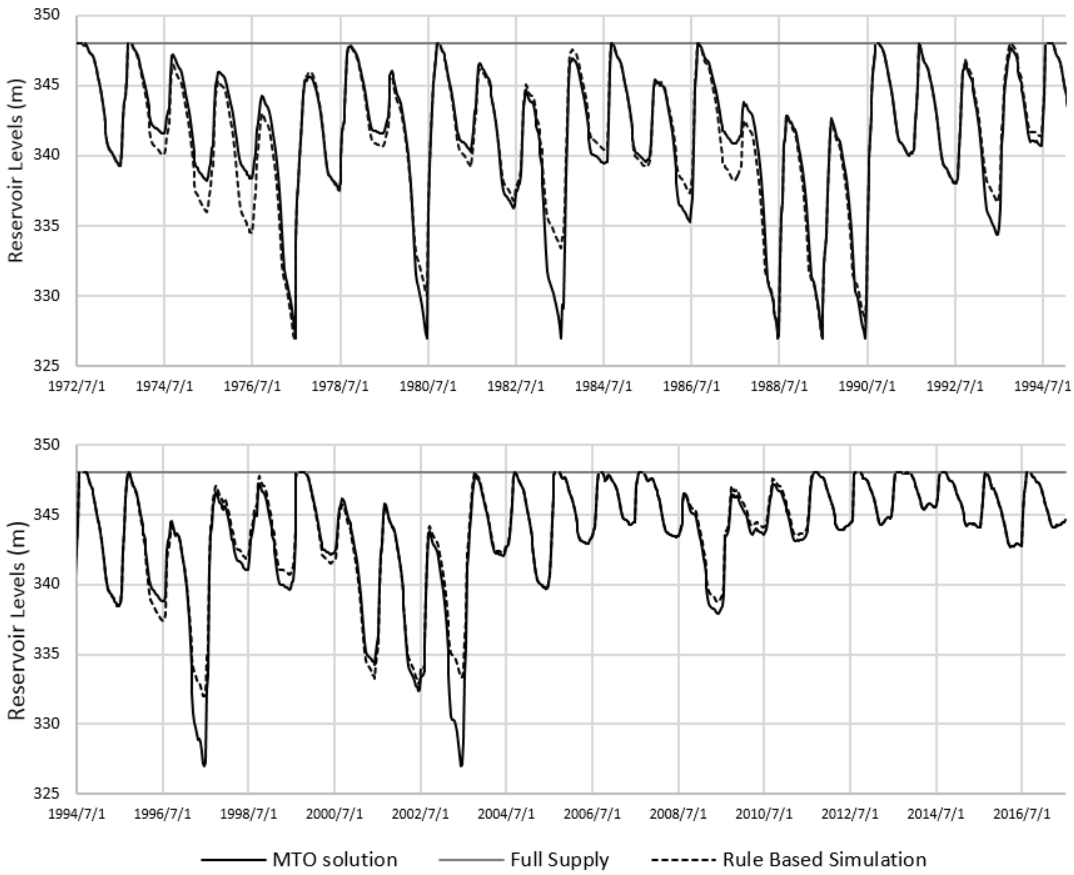

Figure 9. Comparison of Barna reservoir levels from MTO solution and the proposed rules.

It should be self-evident that the closer the rule-based simulated levels are to the MTO results, the better the rules. In this sense, the MTO solutions provide both the benchmark for testing the proposed operating rules, as well as the foundational database for the development of the same rules (assuming sufficient number of years of inflow series was available in a given study). The above approach can therefore be useful when defining the shape and sizes of reservoir operating zones, reducing the reliance on the judgement of the modeler, which is currently prevalent in the industry.

When there is more than enough water, as in the last 6 simulated years, the MTO and the rule-based simulation results are identical, as they both correspond to the results that would be obtained from the Standard Operating Policy (SOP) which provides water on an "as needed" basis. However, such policy would tend to result in a premature emptying of storage in dry years. The important distinction is that the two solutions provided in this work (both the MTO and the rule-based solution) always maintain a minimum of 50% of target demand in each simulated week, and follow a reasonable water rationing policy in dry years, thus safeguarding the irrigators from crop failure, which has been the principal objective of the proposed operating rules.

5. Conclusions and recommendations

This paper demonstrates a methodology to create short-term reservoir operating rules and water use rationing policies based on analyzing the results of long-term optimization based on perfect foreknowledge of inflows. The approach holds out a promise to generate efficient reservoir operating rules in complex multi-reservoir multi-purpose systems were sufficient and reliable input data are available. The study was based on the use of the WEB.BM model which can be used either as a planning or an operational tool that can take into account hydrologic channel routing as constraints built into the optimization process[15]. The results of this study demonstrate a potential to achieve outstanding results based on comparing the model output with the results of the MTO run, which can be used as a benchmark to gauge the quality of the proposed operating rules. Future studies can focus on more comprehensive statistical analyses of the model output and possible use of stochastic inflows series that have similar relevant statistics as the historic series, thus providing lengthy statistical sample of MTO solution for further investigation and analyses.

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Data and model availability

The WEB.BM model is a web application that uses the COIN-OR library of linear programming solvers. In its most basic form, the model can be accessed without charge at www.riverbasinmanagement.com requiring only an email address and a password for registration and access, resulting in the creation of a personal workspace within the application for each registered user. The WEB.BM model is also unique in its capability to include hydrological channel routing as constraints into the optimization process, as demonstrated in the numerical examples and instructional videos that are available from its web site. The data used in this project can be provided upon request.

Conflict of interest

The author declares no conflict of interest.

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