Data envelopment analysis of reservoir system performance

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Abstract

In long-term performance analyses of water systems with surface reservoirs for different operating scenarios, the analyst (or decision maker) is faced with two connected problems: (1) how to handle the extensive output of the simulation model and derive information on the scenarios scores for a prescribed set of performance criteria, and (2) how to compare scenarios in a multi-criterial sense while identifying the most desired. The data sets may overburden the analyst, while an evaluating procedure may be subjective due to personal preferences, attitudes, knowledge and miscellaneous factors. The data envelopment analysis (DEA) approach proposed here seems to be reliable in treating these situations, and sufficiently objective in evaluating and ranking the scenarios. Certain performance indices are defined as evaluating criteria in a standard multi-criterial sense, and then virtually divided into scenarios' output and input measures. By considering scenarios as product units, the DEA optimizes the weights of inputs and outputs, computes productivity efficiency for each unit, and rank them appropriately. Omitting the analyst's personal judgment on the technical parameters that describe system's performance restricts, in this way, the influence of the decision maker. A case study application on the reservoir system in Brazil proved that a methodological connection for solving decision problems with discrete alternatives really exists between the DEA and standard multi-criteria methods.
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1. Introduction

The reservoir system long-term operation is most often analyzed with a simulation model. Such a model must be capable to emulate the system behavior for various management scenarios and applied strategies of the reservoirs' control. The model must handle complex priority schemes in water allocation, treat both consumptive and non-consumptive water uses, and supply the user with reports on water balances at reservoirs and control points of interest. The simulation itself is a difficult task because it usually requires a comprehensive data preparation of the hydrologic part, such as the inflows, precipitation, evaporation, and demands, as well as the operational part, such as the system configuration, simulation parameters, rule curves for reservoirs, and priorities in allocation. Even when data has been prepared correctly and the model has been run with success, particular requirements exist in managing and interpreting its output. Namely, at the end of one typical simulation, the analyst can easily be disoriented by rich but distributed information contained in series of data describing supplies and shortages at demand points, reservoir storage levels and balances, flows in rivers and canals, and various summary reports.

Well-known models for reservoir system simulation are generally equipped with a graphical interface, which makes the results transparent and helps the analyst to derive certain conclusions on system performance. However, if several operating scenarios have to be compared, an output report might be significantly enlarged, and difficulties arise in cross-referencing important data. In reality, scenarios are usually characterized by different priority schemes related to demands and the reservoirs control strategies. With an increase in the number of reservoirs and/or demand points, reports on system operation even for very few scenarios may overburden the analyst, and make almost impossible deriving the right conclusions on advantages and disadvantages of simulated operating strategies. We argue that a new paradigm is required to compare scenarios and point to the best or most desirable one. A central issue is to define criteria set that would govern a comparison process. Because criteria are usually conflicting and of different importance, criteria weighting must be performed preferably by the analyst, or decision maker. A reasonable dilemma might be whether to compare scenarios in an unbiased manner, or to use the subjective judgments of the decision maker? Rather, the question is will the decision maker correctly and consistently compare scenarios, or whether it is more opportune to avoid the decision maker and let the scenarios decide for themselves which one is the best ? (Doyle [1]).

In this paper, we address the described problem and propose a methodology of evaluating the long-term performance of the reservoir system under different scenarios by multi-criteria analysis based on data envelopment analysis (DEA) (Charnes et al. [2]). We first define a number of indices of system performance: supply reliability, resiliency, vulnerability, and the dispersion of reservoirs' storage levels. As performance constructs, they enable the analyst to evaluate and rank scenarios in an unbiased manner once the scenarios are simulated, system performance indices computed, and necessary data is integrated into a multi-criteria analysis framework. The performance indices are adopted as a criteria set and treated within the DEA context.

Originally developed to evaluate efficiency of product units with multiple inputs and multiple outputs, the DEA method is recently used as a discrete multi-criteria decision making (MCDM) method as well. By implementing a methodological connection that allows the decision (performance) matrix typical for standard MCDM methods to be used as a productivity matrix typical for DEA (see, e.g., Sarkis [3]), we solve the comparison problem and measure the efficiency of scenarios searching for the most efficient and ranking the others. We argue that the most efficient scenario identified by the DEA may be considered the best in a MCDM sense. For the sake of completeness, several MCDM methods have been also used to

check the result obtained by the DEA. A comparative analysis performed for a real system case example showed a good conformance of the scenarios ranking obtained by DEA and standard MCDM methods, and indicated that a methodological connection exists.

The proposed methodology has been applied in evaluating several long-term management scenarios for the selected two-reservoir system in Brazil. The chain of consecutive tasks is performed to come-up to the final task of the analysis—to compare scenarios. With data on system configuration and with parameter sets and rules that govern the system operation for a 30-year period, multiple simulations have been performed by the network LP-based model MODSIM (Labadie [4], Porto et al. [5]). A system operation is simulated for each scenario, and the selected model output has been evaluated by another programming system (SYSPER—acronym of 'System Performance') to determine failures and non-failures in meeting specified system targets. Various demands are analyzed at the system level with adopted schemes of accounting for the total demands, total supplies, and other data that describe system performance. Tolerant shortages are specified to distinguish failures and non-failures, that is to enable computing behavioral characteristics of the system for each scenario such as: total supply reliability, resiliency, and vulnerability. An additional performance indice is defined to provide for measuring the reservoirs ability to follow their own rule curves and determine the stability of each reservoir performance, e.g. the recognition of extreme drawdowns related to hazard operating conditions such as extreme depletions during long drought periods.

The aforementioned system characteristics are adopted as performance criteria and used afterwards for ranking the scenarios. The synthesis part of the methodology requires creating the performance matrix with cross-reference data on system performance for analyzed scenarios. This matrix serves as the starting point for the application of DEA, computing scenarios efficiencies, and the final ranking. Two versions of the DEA method have been used to accomplish the task: the original CCR model developed by Charnes et al. [2], and its reduced version RCCR proposed by Andersen and Petersen [6]. To verify the results obtained by the DEA, the following MCDM methods have also been used: the Analytic Hierarchy Process (AHP) [7], the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [8], the Compromise Programming (CP) [9], the Preference Ranking Organisation Method for Enrichment Evaluations (PROMETHEE) [10], and the Simple Product Weighting Method (SPW) [11].

We first present the basic characteristics of two proposed DEA models (Section 2). Then we introduce four indices proposed as the principal criteria for measuring the reservoir system performance and evaluation of the water management scenarios (Section 3). A description of proposed methodology (Section 4) is followed by an example application (Section 5). The main conclusions (Section 6) close the paper.

2. DEA fundamentals

The DEA is a method based on linear programming, which is becoming an increasingly popular management tool. It is commonly used to evaluate the efficiency of a number of 'units' such as a group of producers, banks, or hospitals characterized by multiple inputs and outputs. In fact, the DEA is suitable for evaluating almost any relatively homogeneous set of units, but nowadays it is also recognized as a decision aid in multi-criteria analyses of discrete alternatives.

In contrast to statistical approaches characterized by evaluations of units relative to an average unit, DEA is an extreme point method that compares each unit to all other units with weights chosen to favor the unit under consideration. The evaluation strategy for DEA develops from the fact that the usual measure

of efficiency, given by the ratio of output to input, is inadequate if outputs and inputs are multiple and possibly incommensurate. Farrell and Fieldhouse [12] addressed the problem by constructing a hypothetical efficient unit as a weighted average of the efficient units to act as a comparator for an inefficient unit. This approach was improved in the following decades in various directions. The one, which relates to imbedding DEA into a multi-criteria decision-making paradigm is of interest here and will be repeated shortly due to the work of Sarkis [3].

It was Stewart [13] who has contrasted the traditional goals of DEA and MCDM. More recently, Doyle and Green [14] and Khouja [15] used a methodological connection between MCDM and DEA by defining maximizing criteria (benefits) as outputs, and minimizing criteria (costs) as inputs; max/min criteria are parts of MCDM terminology, while outputs/inputs are their equivalents in DEA terminology. By identifying whether a criterion is minimizing or maximizing, it is possible to consider it as input or output in the DEA model, respectively.

DEA models the productivity for a given unit by simultaneously utilizing weighted amounts of outputs and inputs. If unit is considered an alternative from the alternative set, and outputs are values for maximizing criteria, and inputs are values associated with minimizing criteria, then by using notation of Doyle and Green [16] and terminology from the MCDM field (e.g., 'alternatives' and 'criteria'), the Eq. (1) can be used to represent the efficiency of unit s using the weights of the test-alternative k.

$$E_{ks} = \frac{\sum_y O_{sy} v_{ky}}{\sum_x I_{sx} u_{kx}}. \tag{1}$$

O_{sy} is the value of maximizing criteria y for alternative s, and I_{sx} is the value for minimizing criteria x for the same alternative s. The weights assigned to alternative k for maximizing criteria y and minimizing criteria x are v_{ky} and u_{kx}, respectively.

The fact is that the Doyle and Green approach based on cross-efficiency (1) has not been widely accepted in the DEA literature. Charnes et al. [2] recognized the difficulty in seeking a common set of weights in (1) to determine relative efficiency. They recognized the legitimacy of the proposal that units might value inputs and outputs differently and therefore adopt different weights, and proposed that each unit should be allowed to adopt a set of weights, which shows it in the most favorable light in comparison to the other units (Dyson and Thanassoulis [17]). Under these circumstances, the efficiency of a test unit k can be obtained as a solution to the following problem: Maximize the efficiency of unit k subject to the efficiency of all units being less then or equivalent to 1. The variables of this problem are the weights, and the solution produces the weights most favorable to unit k and also produces a measure of efficiency of k (that was maximized).

In MCDM terminology, the problem is to maximize the efficiency of a test alternative k, from among a reference set of alternatives s, by selecting the optimal weights associated with the measures identified as the output (maximizing criteria) and input (minimizing criteria). A related formulation of the problem is non-linear and is given by model (2)

$$\max \quad E_{kk} = \frac{\sum_y O_{ky} v_{ky}}{\sum_x I_{kx} u_{kx}}$$

$$\text{s.t.} \quad E_{ks} \leqslant 1 \quad \text{for all alternatives } s \text{ (including } k\text{)}, \tag{2}$$

$$u_{kx}, v_{ky} \geqslant 0.$$

This equation is the starting point in the development of various DEA models described in pertinent literature. Two models presented below are used for evaluating reservoir operation scenarios. The first is

known as the basic DEA model referred in literature as CCR (Charnes et al. [2]); the other is a reduced version of CCR, and is entitled appropriately as RCCR (Andersen and Petersen [6]).

2.1. CCR—basic DEA model

The equivalent linear formulation of model (2) can be obtained if the denominator in (2) is set to 1 and transferred into the constraints part of the model (see Charnes et al. [2]). This way, the following linear program is obtained:

$$\max \quad E_{kk} = \sum_{y} O_{ky} v_{ky}$$

$$\text{s.t.} \quad E_{ks} \leqslant 1 \quad \text{for all alternatives } s \text{ (including } k),$$

$$\sum_{x} I_{kx} u_{kx} = 1,$$

$$u_{kx}, v_{ky} \geqslant 0.$$

(3)

Program (3) has to be solved s times, once for each alternative from the alternative set. Index k corresponds to the so-called 'test' alternative, that one for which the efficiency is optimized by solving the corresponding program (3). The u's and v's are variables usually constrained to be greater than or equal to zero as given in the last inequalities of (3). This constraint may induce situations in which some inputs or outputs are totally ignored in determining the efficiency. To prevent such an outcome, in many DEA formulations instead of zero some small positive quantity ε is defined on right-hand side of the inequalities in (3).

The solution to model (3) gives a 'local' optimal efficiency of the alternative k and set of weights leading to that solution. The optimal value E_{kk}^*, at most, can take value of 1. If $E_{kk}^* = 1$, then no other alternative dominates k by efficiency, and an alternative k is on the optimal frontier. If E_{kk}^* is less than 1, an alternative is not on the optimal frontier, which indicates that at least one other alternative is more efficient (even if alternative k selects its optimal weights determined by model (3)).

By solving the CCR model for each alternative, efficiencies for alternatives are computed, and it is then possible to perform a final ranking by ordering alternatives by decreasing values of efficiency. The best alternative is the one with the efficiency 1, and the worst is the one with the lowest value of efficiency.

2.2. RCCR—reduced basic DEA model

The notion of efficiency, as modeled in CCR, is faced with 'smoothing effects' on the efficiency frontier. Namely, the CCR does not always provide good discrimination among alternatives, which means that a number of alternatives may have an efficiency value equal to 1; so, it is not possible to select the one as the best. The issue has been addressed in different ways and a number of techniques have been proposed to solve the problem. The one, which is proved efficient in various applications, is the variation of the basic CCR model proposed by Andersen and Petersen [6]. To achieve better discrimination among alternative efficiencies, they reduce the original CCR by removing the test unit from the constraint set and leaving

the rest of the DEA model unchanged. The resulting model being the reduced version of the CCR was entitled appropriately as RCCR. The formulation of this model is given as

$$\max \quad E_{kk} = \sum_y O_{ky} v_{ky}$$

$$\text{s.t.} \quad E_{ks} \leqslant 1 \quad \text{for all alternatives } s \text{ (excluding } k\text{)},$$

$$\sum_x I_{kx} u_{kx} = 1,$$

$$u_{kx}, v_{ky} \geqslant 0.$$

(4)

Model RCCR allows for local efficiencies to be greater than 1. In this way, it enables that not only non-efficient alternatives may be ranked, but efficient units as well (those that are usually smoothed by efficiencies equal to 1 by the CCR model).

3. Measures of reservoir system performance

Long-term performance of the reservoir system is typically measured by an evaluation of the volumetric flows of water through a system, including those conserved in reservoirs. It was shown that the system's performance might efficiently be measured with respect to some prespecified targets and preferences [18–21]. By defining the tolerant shortages in the water supply, or acceptable deviations from the prescribed reservoir rule curves, it was also shown that it is possible to identify the so-called favorable and not-favorable system statuses and to compute various indices of system performance (see, e.g., Hashimoto et al. [18], Srdjevic [19]).

The performance measures typically used in long-term water management analyses are safe yield (guaranteed water), shortage index, reliability, resiliency, and vulnerability, to be defined later. Formal descriptions vary and are the most often problem dependent. Measures described below are constructed to represent the total system performance, not a performance at particular supply points. In other words, the system capacity in a total supply is considered, with the only exception that the dispersion coefficients of the reservoir storage levels are used to complete a representation of system's behavior.

To create a common framework and notation in constructing various performance indices, assume that the system operation is simulated over period T consisting of N_Y years. By adopting a month as a unit time step, the total number of time steps is $N_T = 12N_Y$. Let the number of demand points in the systems be K, and the number of reservoirs be L.

3.1. Reliability

The total supply reliability of the system is a probability that the total system supply is satisfactory; that is, the supply is within a tolerant shortage $\varepsilon_{\max}$. For example, satisfactory can mean that the total system demand D_i in given month i

$$D_i = \sum_{k=1}^{K} d_{ki}$$

(5)

must be met at least 90%, which is equivalent to a tolerant shortage of $\varepsilon_{\max} = 0.10$. A summation in (5) is performed over K demand points, and d_{ki} is a demand at point k in month i.

Mathematically, reliability is defined as

$$\alpha = \frac{1}{N_Z} \sum_{i=1}^{N_Z} (1 - Z_i).$$
(6)

Z_i is a zero-one variable which takes value $Z_i = 1$ if delivery is not satisfactory (e.g., shortage is greater than $\varepsilon_{\max}$); otherwise, $Z_i = 0$. Summation (6) is performed only over months in which the total system demand is greater than zero. The total number of these months is denoted as N_z. If at least one point within a system represents municipal and/or industrial demand, usually required continuously throughout the year, the value of N_Z equals N_T. A less rigorous definition of supply reliability allows a summation (6) for all months; that is, to use N_T instead of N_Z.

3.2. Resiliency

Resiliency is a performance indicator that describes how quickly a system is likely to recover from failure, once failure has occurred. Following the notation given above, due to Hashimoto et al. [18] the following coding scheme may be adopted:

(a) $\quad \varepsilon_i \leqslant \varepsilon_{\max} \rightarrow X_i \in A \quad \rightarrow \quad Z_i = 0,$
$\quad\quad \varepsilon_i > \varepsilon_{\max} \rightarrow X_i \in F \quad \rightarrow \quad Z_i = 1,$

(b) $\quad X_i \in A \wedge X_{i+1} \in F \quad \rightarrow \quad W_i = 1,$
$\quad\quad\quad$ -otherwise- $\quad\quad \rightarrow \quad W_i = 0.$

Zero-one variable Z describes the system behavior related to supply in a given month and is defined as described above. Zero-one variable W is introduced to indicate the system's transition into 'new behavior' in the next month. A and F denote acceptable and unacceptable system behaviors, respectively. These are dynamically distinguished for each month by dividing the total supply by the total demand and comparing the obtained value with the value of tolerant shortage $\varepsilon_{\max}$ X_i is the system supply capability during month i. Note that 'otherwise' relates to cases: (1) $X_i \in A \wedge X_{i+1} \in A$, and (2) $X_i \in F \wedge X_{i+1} \in A$.

The average length of time while a system's performance remains unacceptable once it becomes unacceptable is given as

$$\overline{T}_F = \sum_{i=1}^{N_T} Z_i \Big/ \sum_{i=1}^{N_T} W_i.$$
(7)

The nominator in (7) expresses the total number of months when the system was in status F, and the denominator is the number of system's transitions from A to F status; that is, the number of failure events.

Resiliency γ is defined as the reciprocal value of $\overline{T}_F$

$$\gamma = 1/\overline{T}_F.$$
(8)

The higher value of γ indicates a more resilient system. Note that in the case when all shortages in the supply are under tolerant limit, that is

$$\sum_{i=1}^{N_T} Z_i = 0$$

then the system is fully resilient ($\gamma = 1$).

3.3. Vulnerability

In reservoir management, failures are very unlikely to be of the same magnitude and importance. A failure with a deficit of 0.5×10^6 m^3/day (half a million of cubic meters per day) from a 10×10^6 m^3/day target does not present the same consequences as a deficit of 5×10^6 m^3/day from the same target.

There are various definitions of vulnerability as the reservoir system performance indicator (Hashimoto et al. [18], Srdjevic [19], Burn et al. [20]). The one presented by Djordjevic [22] is modified and used here. It defines the system vulnerability as a multi-year average of ratios of the amount of water delivered relative to the amount of water required.

If the total system demand and the total system supply in a given year j are defined as D_j and Q_j, respectively, then vulnerability is computed as

$$v = \frac{1}{N_Y} \sum_{j=1}^{N_Y} \left(1 - \frac{Q_j}{D_j} \right). \tag{9}$$

The greater the value of the supply, the less vulnerable the system. The maximum vulnerability of 1 is obtained when all supplies during period T are zero. The system is not vulnerable only if all demands in all years are fully satisfied; both cases are rather theoretical. A good rationale could be to consider vulnerability of $v = 0.20$ as acceptable.

3.4. Dispersion of reservoir storage levels

A performance of reservoirs can be analyzed in different ways. The one used by Srdjevic [19] determines the dispersion of simulated reservoir storage levels from initially defined operating rule curves in an attempt to iteratively reduce dispersion and create max/min envelopes of rule curves for later refinements. In the case when rule curves do not exist, and reservoirs are to be operated with lower priority of conserving water regarding higher priorities of points with specified consumptive demands, a dispersion of storage levels with regard to average values (both simulated and then computed) can be considered as a system performance indicator which describes the stationary structure of the stochastic process which represents reservoirs' level changes in multi-year periods.

In case there are specified operating rule curves, reservoir performance should be analyzed as a cyclic process with monthly oscillations during a year in a multi-year period. Otherwise, virtual rule curves can be specified to correspond to a certain fixed target level of low priority such as the maximum reservoir capacity. This way, a simulation model might be adapted to record reservoir levels as a straightforward non-cyclic process over $N_T = 12N_Y$ consecutive months and be allowed to determine the following

statistical parameters afterwards:

$$\text{Average storage level :} \quad \bar{x}_l = \frac{1}{N_T} \sum_{i=1}^{N_T} x_{li}, \quad l = 1, 2, \ldots, L, \tag{10}$$

$$\text{Variance of storage levels :} \quad \sigma_l^2 = \frac{1}{N_T} \sum_{i=1}^{N_T} (x_{li} - \bar{x}_l)^2, \quad l = 1, 2, \ldots, L, \tag{11}$$

$$\text{Variation coefficient for storage levels :} \quad cv_l = \frac{\sigma_l}{\bar{x}_l}, \quad l = 1, 2, \ldots, L. \tag{12}$$

By adopting such an approach, the variation coefficients cv_l ($l = 1, 2, \ldots, L$) should be derived for each reservoir separately and used as the system's performance indices. This approach is logical because the reservoirs' capacities and importance in local and global water allocation may significantly differ. For many reasons, resulting statistics given by (10)–(12) may greatly vary from reservoir to reservoir. The general strategy in operating reservoirs in a long-term sense in absence of rule curves should be to tend to minimize variation coefficients cv_l computed with respect to a multi-year average reservoir storage level. In this way, the dispersion coefficient may be considered as minimizing criterion in evaluating reservoir and system performance. Consequently, the quality of a particular scenario may be considered better if the dispersion coefficients are smaller.

4. Ranking management scenarios by DEA

An analysis of the reservoir system performance for a given set of management scenarios means that multiple simulations of system operation should be performed by a certain computer model, followed by the creation of the multi-criteria decision-making environment, and concluded by a consistent comparison process which will produce the final ranking of the scenarios and point to the 'best'. If possible, a simulation model would be instructed to record the desired information on system states during the simulation and enable in-turn computation of a desired set of system performance indices. This is, however, rarely possible because well-known simulated models, such as MODSIM [4], or one of its versions MODSIM-P32 [5], are available only as executive codes that do not permit additional programming or creating desired output files for further computations. This difficulty may be overcome by using selected output files from simulation models as they are, and by forwarding them to the other models specialized for a profound analysis of system performance. This way, it is possible to derive the desired information and use it in multi-criteria analysis. Given the context, the first model (simulation) may be considered as general, and the other (performance analysis) as problem oriented.

Here, we propose a methodology of an integrated reservoir system simulation and multi-criteria analysis of a system's performance for different scenarios, Fig. 1. A methodology comprises three straightforward phases. Phase 1 is considered as 'introductory' and concerned with problem formulation and data preparation. The first set of activities identified in Fig. 1 as 'Scenarios' describes in detail all operational scenarios, including priority schemes for consumptive and non-consumptive water allocation. For evaluating the system performance, a set of criteria has to be specified as the performance constructs described in Section 3. In general, other constructs may be used but it is essential that they should represent the complexity of the intuitive or justified preferences of the decision-maker. This part of Phase 1 is identified
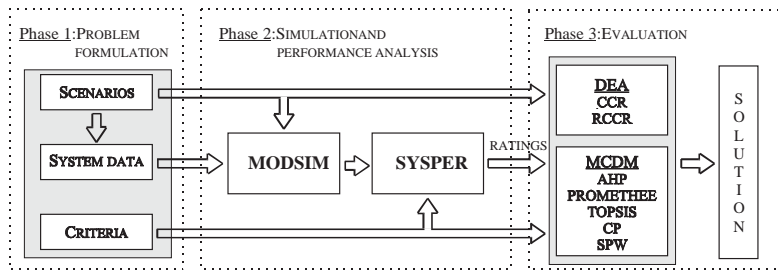
Fig. 1. DEA methodology.

by 'Criteria'. In the 'System Data' part of this phase, the system configuration should be defined including its technical characteristics such as: (1) for reservoirs: max/min storage capacities, initial volumes, area-volume functions, and operating rule curves; and (2) for rivers and canals: max/min flow capacities and minimum flow requirements. The hydrological time series of inflows, precipitations and evaporations, as well as the demand distributions and other water requirements should complete 'System Data', accompanied with specific parameters that enable the running of the simulation model.

Phase 2 is considered an analysis in which the model simulates scenarios and generates reports on the system performance containing multi-year reservoir storages, river flows, and allocation of water to the users. As indicated in Fig. 1, the MODSIM model is proposed to perform this task. Proper handling of its output enables the reformatting of selected data files and running the other model that computes performance indices for the system defined in Section 3. This model is identified as SYSPER in Fig. 1. It serves as a generator of scenarios' scores with respect to performance indices; that is, it computes entries of the productivity/decision matrix used in the final phase.

Of particular concern is the simulation part of analysis; that is, a use of a specific river basin model that enables long-term simulations of a multi-reservoir system operation. The network model MODSIM suggested here and used in our study is justified in many applications worldwide. It possesses a good interface and is extremely fast, even when simulating large-scale systems with hundreds of control points and links (reservoirs, supply points, junctions, river sections, etc.). With relative ease, MODSIM permits an extraction of parts from its output for additional performance analysis by models such as SYSPER used in our study. This issue is of great importance in multi-criteria analysis of multiple scenarios because the simulation output may consist of a tremendous amount of data that is impossible to handle properly and to extract necessary information on system performance.

Phase 3 is the 'evaluation' in which previously selected criteria are differentiated into two groups as required by DEA. Minimizing criteria (vulnerability and dispersion of reservoir storage levels) and maximizing criteria (reliability and resiliency) are considered as virtual 'inputs' and 'outputs', respectively. Entering scores computed in the previous phase into a productivity matrix enables cross-referencing criteria and scenarios. Any arbitrarily selected DEA model requires creating and solving a set of linear programs, one for each scenario. If the CCR model is selected, a set of programs given by (3) should be generated; in the case of RCCR, a corresponding set of programs is described by model (4). In either case, linear programs should be generated automatically and formatted according to the requirements of a specialized LP solver. A solution for each program is the maximum efficiency of the related scenario, as well as a set of the importance weights of the criteria for which this efficiency is obtained.
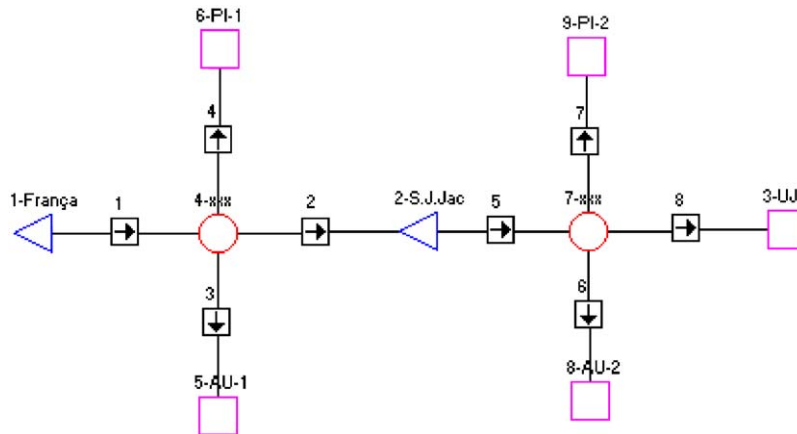
Fig. 2. Case reservoir system (screen taken from MODSIM-P32 interface).

In the final stage of the methodology, necessary data should be collected followed by ranking the scenarios by efficiency. The first ranked is considered the 'best', or most desired in a multi-criteria sense.

Several standard MCDM methods are indicated in Fig. 1 as benchmark tools for validating the derived DEA solution. They are, however, not a part of the proposed methodology.

5. Case study application

5.1. Phase 1: Problem statement, setting the evaluation criteria and creating scenarios

Given is the reservoir system in the Paraguacu river basin in Brazil, Fig. 2, which consists of reservoirs Franca and Sao Jose de Jacuipe with maximum capacities of 24 and 355 millions of m^3, respectively. For given historical data in period 1930–1959 characterized by long droughts, and estimated demands for planning period 2001–2030 at 5 delivery points within the system, the total of 6 long-term management scenarios is created. The problem is to evaluate the scenarios' quality over a 30-year period; that is, to measure selected indices of system performance and conclude in an unbiased way which scenario is most desirable. Performance indices described in Section 3 are adopted as evaluation criteria for using DEA and selected MCDM methods.

It should be noted that the use of 6 management scenarios as a test case is considered useful to illustrate part of the numerical experimentation results only, not to fully demonstrate where the real strength of a technique like DEA lies. Obviously, if there are only 6 possible scenarios, management should be evaluating and examining each holistically, possibly bringing non-quantitative societal goals into account. The real value of and 'objective' method such as DEA is to screen through large numbers of potential scenarios to select a few good efficient alternatives to present to decision makers. In this particular case study example, by taking only 6 scenarios, it was possible to perform a coherent comparative analysis of DEA and several standard MCDM methods; that is, to avoid exhaustive computations and leave it for additional validation of the proposed approach. In practice, one may start with a comprehensive DEA

Table 1
Demands and priority schemes for scenarios

Node	Name	Demand	Scenario/PRIORITY					
		(1/s)	S1	S2	S3	S4	S5	S6
5	AU-1	190	1	1	1	1	1	1
6	PI-1	70	4	6	6	4	2 (distr)	2 (distr)
8	AU-2	525	1	2	2	1	6	6
9	PI-2	700	4	4	4 (550)	4 (distr)	8 (distr)	8 (distr)
3	UJ	200	8	20	20	8	20	20
1	FRANCA res.		10	10	10	10	4	4
2	S.J.JACUIPE res.		15	15	15	15	15	8 (rule)

Explanation: Municipal supply (AU-1, AU-2); Irrigation (PI-1, PI-2); System outlet streamflow requirement (UJ); (distr)—distribution of irrigation demands as given in Table 2; (rule)—rule curve for Sao Jose de Jacuipe reservoir as given in Table 2; Nodes 4 and 7 are confluence points and are excluded from node list since have no influence in scenarios' analyses (cf. Fig. 2).

evaluation of a large set of possible scenarios, reduce this set by identifying a reasonable number of the most efficient alternatives (say 6, as described here) and then, if required, to repeat the evaluation of the selected scenarios with DEA, combined with the preferred MCDM method(s).

The system configuration presented in Fig. 2 and the main data on management scenarios are replicated from Porto [23]. Two types of demands are distinguished. Consumptive demands are defined at four points based on estimates of water requirements for the municipal supply and irrigation in the year 2030. Non-consumptive demands are usually coded as storage rule curves; that is, as storage targets at reservoirs for each particular month. Except in one scenario, the rule curves are specified at maximum reservoirs' capacities in all months and all years, but with low priority. In this way, it was possible to model global operational strategy that recognizes a specific hydrological and other natural conditions typical for a semi-arid region where the system is located, and preserves that the consumptive demands are satisfied with a higher priority than the demands represented by the conservation of water in reservoirs.

Main characteristics of the scenarios are summarized in Table 1. The scenarios are generally differentiated by the priority schemes that apply to water users and reservoirs when following their rule curves. Priority numbers given in Table 1 are integers that relate to preferences in the water supplies; the lower the number, the greater the priority for satisfying the related demand. Note that numbers are arbitrarily selected for the reader's convenience but they fully preserve the global preferences in each analyzed case. For example, in scenario 1 it is specified that the municipal demands AU-1 and AU-2 have the first priority (priority number 1). The next priority is assumed to be the same (4) for the irrigation demands PI-1 and PI-2, and the last priority is put to the demand UJ (8). Reservoir Franca should be filled up with a low priority (10), after all higher prioritized demands are met. The lowest priority (15) is given to reservoir Sao Jose de Jacuipe; it is filled-up only after all other demands within a system are met as much as possible.

Water quantities required at demand points are kept fixed, except for scenario 3 in which the irrigation demand at one point is decreased; the value in parenthesis corresponds to a reduced demand as indicated in Table 1. Uniform monthly distributions are applied for municipal and irrigation demand points in scenarios 1–3. In scenarios 4–6, the irrigation demands are varied as noted in Table 1 by applying a

Table 2
Irrigation demand distribution and arbitrary rule curve for larger reservoir

	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov	Dec
Irrigation demands (a)	9.3	8.8	7.7	7.5	5.4	3.4	3.7	7.9	13.3	15.0	9.4	8.6
Sao Jose de Jacuipe reservoir rule curve (b)	50	70	80	90	100	100	100	100	30	30	30	40

Explanation: (a) % of total annual demand; (b) % of maximum reservoir capacity.

Table 3
Decision (performance/productivity) matrix

Scenario MCDM terms DEA terms	Reliability C1 (max) Output 1 (v_1)	Resiliency C2 (max) Output 2 (v_2)	Vulnerability C3 (min) Input 1 (u_1)	c.v.-FRA C4 (min) Input 2 (u_2)	c.v.-SJJ C5 (min) Input 3 (u_3)
1	0.80	0.11	0.18	0.60	0.77
2	0.52	0.23	0.20	0.56	0.74
3	0.51	0.24	0.17	0.51	0.66
4	0.81	0.11	0.18	0.59	0.77
5	0.57	0.26	0.22	0.39	0.72
6	0.18	0.06	0.39	0.39	0.51

Explanation: c.v.—dispersion coefficient defined by Eq. (12); FRA—Franca reservoir, SJJ—Sao Jose de Jacuipe reservoir; C1–C5—criteria (MCDM); Inputs and Outputs (DEA); v_1, v_2, u_1, u_2, u_3—weight coefficients (used in DEA); All data has been computed by program SYSPER (parts of MODSIM-P32 output has been used as input to SYSPER).

distribution pattern given in Table 2. The rule curves at the reservoirs are specified as maximum storage levels except in scenario 6 where the arbitrary rule curve for a larger reservoir is defined, Table 2.

5.2. Phase 2: Simulating scenarios by MODSIM-P32 and computing scenarios' scores

Each scenario is simulated with model MODSIM-P32 [5]. Reservoir capacities are specified in millions m³: França—$C_{max} = 24$, $C_{min} = 1.7$, and Sao Jose de Jacuipe—$C_{max} = 355$, $C_{min} = 20$. To enable the proper balancing of the reservoirs' levels due to significant evaporation losses and severe but intensive rainfalls in the region, the pattern evaporation and precipitation data are used with area–volume curves at both reservoirs to model the related water losses and gains.

The selected simulation results are used as an input to the SYSPER program to compute the reliability of the supply, resiliency, and vulnerability of the system and storage dispersion coefficients for reservoirs. For running SYSPER, a time series of the simulated reservoirs end-of-month storages and end-of-month targets (rule curves) are used together with data on required and supplied quantities at demand points. Computed performance indices are shown in the decision matrix (Table 3).

Table 4
Descending rank orders of scenarios for two DEA models

Scenario	CCR	Scenario	RCCR
3	1.000000	5	1.442329
5	0.997921	3	1.199289
4	0.994582	4	1.022340
1	0.984740	1	0.984740
2	0.884882	2	0.884882
6	0.400281	6	0.400281

5.3. Phase 3: DEA application

The data given in Table 3 are used as a DEA productivity matrix. In the application of the CCR and RCCR models, two sets of linear programs are created as defined by models (3) and (4), respectively. Computed partially optimal weights of inputs and outputs are used to compute the scenarios' efficiencies as presented in Table 4.

The CCR model identified scenario 3 as the most efficient, followed by scenario 5. In the case of the RCCR model, the order of scenarios is reverted. The rest of the scenarios are ranked the same way by both models. Notice that scenario 6 is recognized by both models as least efficient, valued significantly lower than the others. We can explain the rank reversal of the most efficient scenarios 3 and 5 as a consequence of the described differences between CCR and RCCR models. It does not necessarily shed light on the merits or weaknesses of the two models used; we rather argue that parallel use of CCR and RCCR is unnecessary as explained below.

The results obtained by CCR indicate an efficiency of 1 for only scenario 3; so, it is not difficult to point to it as the best. This is, however, rarely the case in practice (see, e.g., Sarkis [3]). More commonly, several units, or scenarios, might posses the maximum efficiency of 1, and there might be no way to distinguish them. The other model, RCCR, enables a better contrasting of the scenarios which is obvious if the top three scenarios in Table 4 are compared by efficiencies. Therefore, RCCR is considered the more confident model, and consequently the result obtained (scenario 5) is adopted as a final solution to the problem.

The other part of the DEA solution is also of interest. We may proceed only with results obtained by the RCCR model and consider the weights of input and output criteria computed as local optima for each scenario. These values are presented in Table 5. For the most efficient scenario 5, criteria reliability, resiliency, and the variation coefficient for reservoir Franca obtained weights different from zero, and the remaining two (vulnerability and variation coefficient for reservoir Sao Jose de Jacuipe) obtained values zero. The solution with zero weights for certain criteria is allowed by constraints contained in the RCCR model. Note that similarly there are one, the two, or three criteria with zero weights obtained in optimizations for other, less efficient, scenarios.

5.4. Comparison of DEA results with results obtained by standard MCDM methods

Several methodologically different MCDM methods are used to perform the same task as DEA. They are listed in Table 6 and described in pertinent literature. In AHP applications, an ideal-mode evaluation has been performed. The CP method has been applied for norm $p = 1$.

Table 5
Computed optimal weights in RCCR model with zero constraints in Ineq. (4)

Scenarios Weights LP variables	Reliability Output 1 (max) v_1 X1	Resiliency Output 2 (max) v_2 X2	Vulnerability Input 1 (min) u_1 X3	c.v.-FRA Input 2 (min) u_2 X4	c.v.-SJJ Input 3 (min) u_3 X5	Efficiency
1	0.984	1.844	5.556			0.984740
2	1.081	1.406	0.353		1.256	0.884882
3		4.977	5.882			1.199289
4	1.269		0.616	1.507		1.022340
5	1.585	2.080		2.564		1.442329
6	1.604	1.913			1.961	0.400281

Table 6
Multicriteria decision making methods

AHP	Analytic Hierarchy Process
PROMETHEE 1,2	Preference Ranking Organization Method for Enrichment Evaluation
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
CP	Compromise Programming
SPW	Simple Product Weighting

All MCDM methods are firstly applied to the decision matrix presented in Table 3 with weights of importance for criteria derived by the DEA-RCCR model for the best scenario 5 (cf. Table 5). Results summarized in Table 7a indicate a good agreement between the DEA and MCDM methods and confirm that there is a strong methodological connection between these two groups of decision tools.

Sensitivity analyses for several arbitrary selected sets of weights indicated again a high conformance of results obtained by the MCDM methods and DEA–RCCR model. For example, if storage variation coefficients for both reservoirs are set to low priority, the ranking of scenarios remains the same (Table 7b), as well as if all criteria obtain the same weights (Table 7c).

6. Conclusions

We have shown how to apply the DEA in an unbiased evaluation of the reservoir system performance for various operating scenarios. A decision-making environment typical for water resources planning and management is assumed, and the evaluation of scenarios is considered as a multi-dimensional problem requiring various decision tools be applied. An underlying assumption is that the simulation models for the reservoir systems generate extensive output files for system configurations including more than one reservoir and several demand points. There is no generally accepted methodology for evaluating the results obtained by such a model, neither is there an approach for comparing the behavioral characteristics of a system for different operational scenarios.

In this paper, a set of indices is defined to enable measuring the long term system performance for a given scenario, which aggregates reservoir control strategies, consumptive and non-consumptive water

Table 7
Scenario ranks

Scenario	DEA		MCDM					
	CCR	RCCR	AHP	TOPSIS	CP($p = 1$)	PROM1	PROM2	SPW
(a) *Criteria weights computed by DEA–RCCR model for best alternative*								
1	4	4	5	5	3	6	6	5
2	5	5	3	3	5	3	4	3
3	1	2	2	2	2	2	2	2
4	3	3	4	4	4	5	5	4
5	2	1	1	1	1	1	1	1
6	6	6	6	6	6	4	3	6
(b) *Arbitrary criteria weights* (0.30, 0.30, 0.20, 0.10, 0.10)								
1	4	4	5	5	5	5	5	5
2	5	5	3	3	2	4	4	3
3	1	2	2	2	3	1	1	2
4	3	3	4	4	4	3	3	4
5	2	1	1	1	1	2	2	1
6	6	6	6	6	6	6	6	6
(c) *Equal criteria weights* (all 0.20)								
1	4	4	5	5	2	5	4	5
2	5	5	3	3	4	4	5	3
3	1	2	2	2	2	1	2	2
4	3	3	4	4	3	3	3	4
5	2	1	1	1	1	2	1	1
6	6	6	6	6	6	6	6	6

demands, various operational constraints, and priority schemes for water allocation. Indices are also considered as a criteria set for comparing scenarios within an integrated DEA/MCDM framework.

A proposed approach is based on a partial evaluation of the simulation model's output for several operational scenarios. The quality of each scenario is measured appropriately to obtain the systems' performance scores, which are then considered entries to the DEA's productivity matrix. This matrix is constructed by scenarios as productivity units (rows), and performance criteria as virtual inputs and outputs of units (columns). Associating criteria to input and output sets is due to a recognized methodological connection of DEA and standard multi-criteria analysis. By considering the minimization criteria as inputs, and maximization criteria as outputs, the performance scores were in turn obtained by the consecutive application of the MODSIM and SYSPER models. The productivity of the scenarios is computed by the two DEA models, CCR and RCCR, while a more sophisticated RCCR model determines the final ranking of the scenarios. Several MCDM methods are then used in additional analyses to check the DEA results. By applying criteria weights of importance derived by RCCR for the most productive scenario, and two arbitrary but reasonable sets of weights, the DEA results are verified at a proof-of-concept level.

Because the DEA-inspired approach is partially based on strict optimisation by linear programming, it can be considered as an objective one. However, it does not eliminate the subjectivity of the decision maker. Obviously, all decision-making must ultimately involve human value judgments, which must be

subjective. The role of the decision maker should never ever be 'skipped' or merely 'minimized'. It would encourage consistency and coherence of decision-making and preserve the elimination of caprice or any wrong attitudes on the part of the decision maker. In real-life decision-making, real objectivity is unattainable, and it is at best a myth. The real merit of procedures such as those described in this paper is to support the selection of a manageable number of efficient alternatives, when the decision maker value judgements are not jet available, to be presented to decision maker for detailed consideration. In the proposed approach, the role of decision maker is assumed to be dominant in creating scenarios and defining which performance criteria to use, and less dominant in an evaluation process itself, at least in part where DEA is used instead. For the sake of completeness, it should be noted that partial involvement of the decision maker in DEA approaches in other fields is well investigated. A final agreement on the real validity of such an involvement does not exist.

Acknowledgements

References

[1] Doyle JR. Multiattribute choice for the lazy decision maker: let the alternatives decide. Organizational Behavior and Human Decision Processing 1995;62(1):87–100.
[2] Charnes C, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. European Journal of Operational Research 1978;2:429–44.
[3] Sarkis J. A comparative analysis of DEA as a discrete alternative multiple criteria decision tool. European Journal of Operational Research 2000;123:543–57.
[4] Labadie JW. MODSIM—River basin network model for water rights pallning. Technical Manual. Colorado State University, USA, 1995.
[5] Porto RL, et al. MODSIM-P32 Manual do usuario. Brazil: Universidade de Sao Paulo; 1998.
[6] Andersen P, Petersen NC. A procedure for ranking efficient units in data envelopment analysis. Management Science 1993;39(10):1261–4.
[7] Saaty TL. The analytic hierarchy process. New York: McGraw-Hill; 1980.
[8] Hwang CL, Yoon KS. Multiple attribute decision making: methods and applications. New York: Springer; 1981.
[9] Zeleny M. Multiple criteria decision making. New York: McGraw-Hill; 1982.
[10] Brans JP, Vincke P. A preference ranking organisation method (the PROMETHEE method for multiple criteria decision-making). Management Science 1985;31(6):647–56.
[11] Triantaphyllou E, Lin CT. Development and evaluation of five multiattribute decision making methods. International Journal of Approximate Reasoning 1996;14:281–310.
[12] Farrell MJ, Fieldhouse M. Estimating efficient production functions under increasing returns to scale. Journal of the Royal Statistical Society Series A 1962;125:252–67.
[13] Stewart TJ. Relationships between data envelopment analysis and multicriteria decision analysis. Journal of the Operational Research Society 1996;47(5):654–65.
[14] Doyle JR, Green RH. Data envelopment analysis and multiple criteria decision making. Omega 1993;21(6):713–5.
[15] Khouja M. The use of data envelopment analysis for technology selection. Computers and Industrial Engineering 1995;28(2):123–32.
[16] Doyle JR, Green RH. Efficiency and cross-efficiency in DEA: derivations, meanings and uses. Journal of the Operational Research Society 1994;45:567–78.
[17] Dyson RG, Thanassoulis E. Reducing weight flexibility in data envelopment analysis. Journal of the Operational Research Society 1988;39:563–76.

[18] Hashimoto T, Stedinger JR, Loucks DP. Reliability, resiliency and vulnerability criteria for water resource system performance evaluation. Water Resources Research 1982;18(1):14–20.

[19] Srdjevic B. Identification of the control strategies in water resources systems with reservoirs by use of network models. Dissertation, University of Novi Sad, Yugoslavia, 1987.

[20] Burn DH, Venema HD, Simonovic SP. Risk-based performance criteria for real-time reservoir operation. Canadian Journal of Civil Engineering (Ottawa) 1991;18:36–42.

[21] Azevedo LGT, Gates TK, Fontane DG, Labadie JW, Porto RL. Integration of water quantity and quality in strategic river basin planning. Journal of Water Resources Planning and Management, ASCE 2000;126:85–97.

[22] Djordjevic B. Cybernetics in water resources management. Highlands Ranch, CO, USA: Water Resources Publications; 1993.

[23] Porto RL. Estudos operativos do sistema Franca - Sao Jose do Jacuipe. Resumo Executivo para a Superintendencia de Recursos Hidricos do Estado da Bahia, 1997.