Methods of risk management (technology and water quality) [Part 2. Examples of application]

Louati M.H., Lebdi F.

in

Iglesias A. (ed.), Moneo M. (ed.), López-Francos A. (ed.).
Drought management guidelines technical annex

Zaragoza : CIHEAM / EC MEDA Water
Options Méditerranéennes : Série B. Etudes et Recherches; n. 58

2007
pages 469-485

Chapter 23. Methods of risk management (Technology and water quality)

M.H. Louati* and F. Lebdi**
*Direction Générale des Barrages et des Grands Travaux Hydrauliques (DGBGTH)
Ministère de l'Agriculture, de l'Environnement et des Ressources Hydrauliques
30, rue Alain Savary, 1002 Tunis, Tunisia
**INAT, 43 Rue Charles Nicole, Cité Mahrajène, 1082 Tunis, Tunisia

Introduction

The availability of, and the demand for water form one of the most complex relationships the mankind is facing. The primary reason for this is the ultimate importance of water for the life on the planet. Under "availability of water" one should primarily underline the limiting amount of water in our hydrological cycle, the uneven distribution of its quantities in space and time, and the crucial role of water in preserving and maintaining the planet's environment and the life on it. By "demand for water" one should consider drinking and agricultural water consumption as the essential preconditions for human life sustenance, as well as the areas of water use which could be considered as contributing factors to the improvement of the quality of life (i.e. non-consumptive household, industrial, navigation, energy production, recreation water demands, etc.).

Another driving factor in the effort to reconcile water availability and demand is water quality. On the one hand, the quality of available water resources determines, to a varying degree, their suitability for different purposes. The quality of water released back to the environment after its use, on the other, influences the extent of environmental pollution and, in turn, prospects for the maintenance of the sustainable use of the water resources in the future. Furthermore, both the use of the available water resources and the release of the used effluents back to the environment have an impact on the environmental balance in the affected areas.

The aforementioned quantitative and qualitative aspects of the balance of this precious resource have been recognized as crucial in the strive to maintain the necessary environmental quality, ensuring at the same time that everyone gets a just share of water of good quality. Unfortunately, the state of the quantitative and qualitative balance of water resources have been degrading due to the decades of irresponsible human actions mainly based on the notion that water, although indispensable, is still a renewable resource which is never going to be depleted.

Objective criteria

The case study system consists of 15 large reservoirs in the Northern part of Tunisia. The reservoirs are mutually interconnected in either serial or parallel fashion, both through natural river reaches as well as man-made water transfers.

The system encompasses 36 individual demand centres grouped into three principal water user types: urban (five demands), irrigation (thirty demands) and environmental (one demand). The demands have been described by two parameters: demand volume and the maximum acceptable supply salinity.

System topology studied indicates that the analyses are to address a rather difficult operations research problem. On the one hand, the system itself can contain multiple reservoirs and demand centres, which can be linked together in an intricate network. On the other hand, the consideration of salinity of reservoir inflows and releases, and thereby allocations to individual demands, adds additional complexity to the operation problem. It is obvious therefore that the optimization problem must apply criteria which will be able to address both the quantity and salinity of reservoir allocations to individual demands. Furthermore, reservoir operating storage targets (rule curves) are considered as an additional objective criterion.

The primary goal of the analyses is to identify the preferable water resource allocation strategies within a complex water supply reservoir system and, at the same time, to derive the respective optimum operating policies of system reservoirs. To achieve this goal, three objective criteria have been defined and adopted for the analyses:

(i) To minimize the supply quantity deficit.

(ii) To minimize the violation (surpassing) of supply salinity thresholds set for individual demands.

(iii) To minimize the deviation of the operating final storage of reservoirs from the predefined final storage targets.

Supply quantity objective

The adoption of this objective criterion is unavoidable since the system serves primarily a water supply purpose. The choice of minimization of supply quantity deficit as opposed to maximizing the allocation for consumptive uses from the reservoirs is due to the fact that the demand volumes are known in advance. In addition, the problem has not been defined as yield estimation but rather an improvement of resource allocation and operating policies of supply reservoirs within a complex reservoir system. In this regard, the supply quantity objective choice of deficit minimization is a preferred one.

Supply salinity objective

Due to the fact that salinity of system allocations plays an important role in many water supply systems we attempt to address this issue in the formulation of the operations research problem to be analyzed. In this respect, each demand centre has been assigned a salinity threshold feature describing the maximum salinity of supply the demand centre deems acceptable. To reflect system's ability to comply with the imposed salinity thresholds, an objective criterion which minimizes the excess salinity of supply allocations has been introduced. In addition to the use of this objective criterion in optimization, a number of related system performance indicators have been defined to assess reliability aspects of system operation upon simulation.

Reservoir storage target objective

In addition to the demand aspect, the derivation of reservoir operating policies also addresses the target storage volumes of the individual reservoirs. The rationale to incorporate a storage target objective criterion is due to the fact that the system being analyzed is assumed to be a pure water supply system. Namely, considering only the demand satisfaction side of system operation it is not possible, for instance, to address the issue of reservoir filling and spill. On the other hand, reservoir operating rule curves are widely in use as guidelines for operating decisions and more complex operating policies are seldom favoured by reservoir operators. In this respect, it is the goal of the work to introduce a possibility to utilize rule curve targets as an additional objective criterion while deriving the optimum operating policies of individual reservoirs. This option also gives a possibility to carry out a comparison between operating policies with and without consideration of operating rule curve (i.e. storage target) objectives. Similarly to the other two objective criteria used in optimization, a number of storage target related system performance indicators have been defined to assess reliability aspects of system operation upon simulation.

Structure of the optimization problem

The main goal of this work is to assess the applicability of a combination of several operations research approaches to a strategic operational problem of complex reservoir supply systems. System topology requires that the adopted approach for the analyses be able to tackle rather complex system configurations. With regard to such a system topology, the focus of the work is limited to the optimization of the long-term operating strategy of a multiple reservoir water supply system. In principle, an operating strategy of such a complex system may be understood as a composition of two main parts:

(i) Reservoir-demand allocation patterns.

(ii) Reservoir operating policies reflecting the aforementioned allocation patterns.

Such a decomposition of the operating strategy is justified by the fact that the original problem is rather complex, thus requiring either huge, if not prohibitive, computational resources to arrive at the optimum solution, or enormous simplifications of the problem to render it manageable at an acceptable cost.

Reservoir-demand allocation patterns are introduced to resolve the problem of demand sharing among groups of reservoirs. In other words, these patterns represent the portions of individual demands each reservoir is targeting. This simply means that each demand is split into its sub-component demands, each of which is supplied by a single reservoir only. The task of optimization is therefore to identify those demand sharing patterns which would lead to the best allocation of water resources within a system.

Once reservoir-demand allocation patterns have been derived, the optimization of individual reservoir operating policies can be carried out. This process is therefore based on the assumption that the derived allocation patterns have to be complied with in policy optimization. As a consequence, the obtained operating policies will preserve the imposed reservoir-demand allocation patterns.

Uncertainty is inherent in the operation of any water resource system and since the nature of the problem in hand is to derive a long-term operating strategy of a reservoir system, the stochasticity of reservoir inflows is considered. This is however not to say that stochasticity of other factors influencing the operation of the system is diminished. It is only decided that the uncertainty of the inflow processes is sufficient for the case being analyzed. With regard to the temporal discretization, the analyses are limited to monthly time steps assuming the stationarity of the stochastic properties of monthly river flows (i.e. the probability distribution of a stochastic process is not changing over time). Monthly water demands, on the other hand, are assumed to be deterministic and considered to be recurring in annual cycles. Since the chosen monthly time base is long enough the required time for the released water to travel between any two serially linked reservoirs and any reservoir and the respective demand centres can safely be neglected.

Optimization problem characteristics

The main goal of the analyses is to derive the best long-term operating strategy of a complex reservoir system. Since the size of such a problem can be prohibitively large (i.e. number of reservoirs and demand centres, the complexity of reservoir-reservoir and reservoir-demand interconnections, consideration of flow stochasticity, and multiple objectives) it is inevitable to opt for some kind of adjustment of, and modification to the problem itself to render it manageable by an appropriate operations research method. Therefore, the adopted methodology to solve the operational problem for such a system, and with respect to the given objectives, falls into the group of decomposition techniques. In essence, decomposition approaches break down a complex optimization problem into a series of simpler tasks. They subsequently employ an iterative derivation procedure to arrive at the respective solution. One common characteristic of almost all the approaches of this kind is, however, that the global optimality of the obtained solution cannot be guaranteed. It is, therefore, necessary to emphasize that the starting point of this work was not to pursue a methodology which would guarantee the derivation of the global optimum operating strategy at any cost, but rather to try and identify a relatively simple and transparent, however yet efficient and effective approach for the analysis of the operation of complex reservoir systems. With this notion in view, the decomposition applied in this study is done at two levels:

(i) Problem decomposition.

(ii) Reservoir system (topology) decomposition.

Problem decomposition

An operating strategy of a complex reservoir system may be understood as a coupling of:

(i) Reservoir-demand allocation patterns.

(ii) Reservoir operating policies reflecting the aforementioned allocation patterns.

Such a decomposition of the problem reduces the complexity of the optimization task and allows that it can be solved with less computational effort. What needs to be ensured when deciding on the approaches to solve these two resulting sub-problems is that the two keep the maximum similarity with regard to the links between them which are broken by decomposition.

Reservoir system decomposition

Each of the two sub-problems can still require formidable computational effort to solve it, especially in cases where the systems being studied are highly complex. Therefore, a general concept of reservoir system decomposition is applied in both sub-problems. The main features of the applied system decomposition approach are:

(i) It is an iterative procedure, with main iterative cycles repeated until a desired convergence is achieved.

(ii) A multiple-reservoir system is decomposed into single-reservoir sub-systems.

(iii) Appropriate optimization/simulation techniques are applied to single-reservoir sub-systems.

(iv) Single reservoirs are entering an iterative cycle of analyses in a predefined sequence.

(v) The interaction between the reservoirs is modelled by an auxiliary model, which is selected on the basis of the type of problem being solved (i.e. reservoir-demand allocation patterns or reservoir operating policies).

General optimization approach structure

Based on the aforementioned description of the problem and its decomposition, the general structure of adopted approach to derive long-term operating strategy of a complex reservoir system can be formulated as follows:

(i) Decompose the problem into resource allocation and policy optimization.

(ii) Decompose the reservoir system into individual reservoir sub-systems.

(iii) Solve the resource allocation sub-problem applying the appropriate optimization method combined with the reservoir system decomposition principles.

(iv) Solve the policy optimization sub-problem applying the appropriate optimization method combined with the reservoir system decomposition principles.

(v) Simulate the operation of the system according to the derived resource allocation patterns and operating policies.

(vi) Evaluate the performance of the system.

Without entering into the details on decomposition (it is introduced earlier in this chapter) and performance evaluation components of the list above, the methods used to solve the two optimization sub-problems and simulation are briefly introduced in the following.

Namely, the resource allocation sub-problem is solved by a genetic algorithm (GA) based search model. The principal idea of a GA search is to sweep the objective function space looking for solutions which bring improvement to the objective function. Genetic algorithms belong to the family of evolutionary methods, which are based on the principles of natural evolution. They work on a family of potential solutions and apply effective recombination rules to known solution candidates to guide their search towards the best solution to the problem. In this specific case, the GA model assumes that a solution is a collection of reservoir-demand allocation targets for the entire system and uses reservoir system simulation to estimate the objective function value for each potential solution to the allocation problem.

The adopted methodology for the optimization of the long-term operating policies for individual reservoirs combines a physical decomposition of the system into individual reservoir subsystems, stochastic dynamic programming (SDP) optimization of a single reservoir operation, simulation and release allocation among each reservoir's water users. Since the SDP model derives the operating policy for a single reservoir (as opposed to the GA model which derives the allocation pattern for the entire system) its application has to be combined with system decomposition, simulation and release allocation. In addition, the developed SDP model utilizes the reservoir-demand allocation patterns derived by the preceding run of the GA.

Finally, simulation of the system operation according to the derived policies is essential due to three reasons:

(i) It is necessary for the evaluation of potential solutions in the genetic algorithm.

(ii) It is an integral component of the stochastic dynamic optimization model.

(iii) System performance evaluation cannot be done without simulation.

Transformation of a multiobjective decision making problem

The consideration of three distinct objective criteria implies that the problem of derivation of system operating strategies belongs to multiobjective decision making analyses. It is however no the intention of this study to address the issue from a strict multiobjective decision making point of view, but rather to transform the problem into a single-objective optimization.

In this respect, the obvious choice is to opt for a composite objective function which would include all three objectives. However, and since the optimization problem has been split into two smaller sub-problems, the ultimate decision on the composite objective has been made so as to combine two objective criteria in deriving reservoir-demand allocation patterns, and different pair of criteria for the optimization of reservoir operating policies:

(i) Reservoir-demand allocation patterns: supply quantity and supply salinity objectives.

(ii) Reservoir operating policies reflecting the aforementioned allocation patterns: supply quantity and storage target objectives.

Another reason for such a selection of composite objectives for the two sub-problems lies in the choice of methods used to solve them. Namely, a genetic algorithm search is used to derive reservoir-demand allocation patterns. A GA search is based on objective function estimation using simulation of system operation and, therefore, it is no problem to develop a simulation model for a single reservoir which is able to simulate both the volumetric and salt balance of water in a reservoir during a time step. Hence, supply salinity objective can be applied to the first problem without difficulty. On the other hand, stochastic dynamic programming is applied to derive reservoir operating policies and considers reservoir inflows as a stochastic process. Thus, SDP describes reservoir inflows as a Markov process through estimation of monthly inflow transitional probabilities. Consideration of salinity would therefore also require that inflow salinity time series is also described as a Markov process, which would impose that joint probability distributions of flow volumes and salinities are estimated. This would however, render a discrete SDP formulation rather complicated. Furthermore, salinity data available for the research show very little variability over the years of record, thus justifying the assumption that the consideration of supply salinity objective only in reservoir-demand allocation sub-problem. That is, the derived allocation patterns would then sufficiently reflect the objective to minimize the violation of supply salinity threshold and would thereafter implicitly incorporate the salinity consideration into the SDP-based operating policies derived within the second sub-problem.

Additional reason for such a division of objective use is in the fact that the genetic algorithm search for the best reservoir-demand allocation patterns is also used to derive the storage targets of individual reservoirs.

Finally, the combination of supply quantity and storage target objectives in SDP optimization of reservoir operating policies completes the combination of the three objectives. In addition, the derived SDP operating policies would reconcile, in a single policy, the aim to maintain the optimum level of supply quantity and salinity, and the desired storage target curve.

System performance evaluation

The optimization approaches applied here employ different combinations of pairs of objective criteria to arrive at the solutions to the respective multiple-reservoir operating problems. That is, the individual objective functions used in the applied approaches all take some form aggregated penalty incurred by the respective monthly decisions on release.

However, the estimate of the objective function value contains no information about the frequency of the system's failing to provide the required service, the duration and severity of potential failures, nor the ability of the system to return to satisfactory operating state once a failure has occurred. These important facets of system performance are widely known as reliability or performance indicators (PI). Performance indicators provide valuable additional information about the respective performance of the entire system. The choice of PIs is primarily problem dependent and can be made from a variety of reliability, risk and other performance related indicators. Consequently, in order to reflect better the most relevant aspects of a particular operating problem, the definition of the adopted performance indicators often varies from one application to another. It is therefore important to point out that no universal definition exists for almost any one of the most frequently used performance indicators.

Therefore, to reflect on those aspects of the operation of the entire system, the alternative optimization approaches developed in this case study are compared not only on the basis of their respective optimization-based objective function achievements but are also weighed with regard to a number of additional simulation-based performance indicators. Namely, once an operating strategy of the system is derived, the system's operation is simulated and the resulting performance is appraised against a number of criteria.

The advantage of the simulation-based performance assessment is particularly pronounced in the operational analysis of multiple reservoir systems where the complexity prohibits the explicit consideration of performance criteria in the optimization process. By adopting this simulation-based reliability appraisal approach, analysts can opt for simpler optimization methods enabling at the same time the application of complex simulation models to obtain detailed information about various operating aspects of the system's performance. Therefore, the evaluation of different operating strategies derived for the case study system is based on this approach.

Since there are three objective criteria adopted, the selection of performance indicators must also reflect the criteria themselves. Therefore, three distinctive sets of performance indicators are defined to provide additional information on the analyzed system performance:

(i) Performance indicators for the supply quantity objective.

(ii) Performance indicators for the supply salinity objective.

(iii) Performance indicators for the storage target objective.

Reliability criteria assessment in evaluation of reservoir performance

Various optimization techniques have been extensively used to derive operating strategies of reservoir systems. Most frequently, the devised optimization models have relied on maximization or minimization of the selected objective criterion to arrive to the best achievable operating policy of the system in question. Similarly, within a multiobjective framework, the proposed approaches have usually utilized repeated optimization analyses concentrated on alternative single criteria while considering the remaining objectives as constraints. In this way, the analysts have been able to construct the trade-off relationships among the estimated achievements of the objectives imposed upon the analyzed system.

Within stochastic optimization concepts the most frequently used objective criteria include either the maximization of the expected system output or benefit function, or the minimization of the expectation of some form of loss function. Utilization of this type of criteria provides the estimate of the expected performance of the system on the long run. However, they cannot shed any light on the frequency of the system's failing to provide the required service, the duration and severity of potential failures, nor the ability of the system to return to satisfactory operating state once a failure has occurred. These important facets of a system's performance are widely known as reliability indicators. Consequently, substantial effort has been put into the explicit consideration of reliability into the optimization of the operation of reservoir systems. It could be said that the most significant in the field started with the work on chance-constrained programming by ReVelle *et al*. (1969), which was further extended by, to name just a few, ReVelle and Kirby (1970), Eastman and ReVelle (1973), ReVelle and Gundelach (1975), Gundelach and ReVelle (1975), Louks and Dorfman (1975), Houck (1979), Houck and Datta (1981), and many others, including the works on reliability programming by Simonovic and Mariño (1980, 1981, 1982).

Recognizing that the simulated estimates of the mean and the variance of the selected performance measure (e.g. output, operating cost) could not provide accurate information about the frequency and magnitude of operational failures, Hashimoto *et al*. (1982) used three additional performance indicators to compare a number of different operating policies of a single irrigation water supply reservoir. They introduced *reliability* to describe how often the system failed to meet the target; *resiliency* to assess how quickly the system managed to return to a satisfactory state once a failure had occurred; *vulnerability* to estimate how significant the likely consequences of a failure might be. Based on simulation of the reservoir's operation over a long synthetic inflow time series, a set of operating strategies was evaluated by deriving trade-offs among the expected loss, reliability, resiliency and vulnerability. For instance, one conclusion that could be drawn from the analyses was that, for the given case study, high system reliability was always accompanied by high vulnerability (i.e. the fewer failures the reservoir had, the higher deficits were encountered in the failure periods). The authors also pointed out that each problem bears its own unique features and, therefore, the selection of appropriate performance indicators should always reflect upon those unique characteristics of the problem.

Similar conclusions were also drawn by Moy *et al*. (1986) in their study of the operation of a single water supply reservoir. They used mixed-integer linear programming to derive trade-off curves among the virtually same three performance indicators presented by Hashimoto *et al*. (1982). Namely, they defined *reliability* as the probability of failing to meet the desired target; *resilience* as the maximum number of consecutive failures prior to the reservoirs return to the full supply state of operation; and *vulnerability* as the maximum supply deficit observed during simulation. The major finding described the relationship between vulnerability and the other two PIs. In general, the results showed that a reservoir would likely exhibit higher vulnerability (i.e. larger magnitude of failures) if it were more reliable (i.e. had fewer operating failures), or if it were more resilient (i.e. had short sequences of repeated failures).

The expensive study of Bogardi and Verhoef (1995) presented a more detailed analysis of the sensitivity of the operation of same three-reservoir Mahaweli river development scheme in Sri Lanka. Using a range of different objective criteria, they optimized the operation of the system by means of SDP and subsequently appraised the derived operating strategies by simulation. In addition to the simulated objective criterion estimates, the comparisons were carried out on the bases of an array of both energy and irrigation related PIs. The set of PIs included (n.b. for each PI, separate estimates were derived for energy and irrigation):

(i) *The number of failure months* was defined as the total number of time steps with the recorded failure to meet the desired target (i.e. failure mode).

(ii) *The number of failures* indicated the number of time intervals consisting of one or more consecutive failure months.

(iii) *The annual occurrence-based reliability* depicted the fraction of years without failure months detected.

(iv) *The time based reliability* was defined as the fraction of the total time period when the system's operation was not exhibiting a failure.

(v) *The quantity based-reliability* was define as the ratio between the total system output and the total target output over the entire simulation period.

(vi) *The period of incident* depicted the mean duration of periods between two failure months.

(vii) *The reparability* described the average duration the system stayed in a failure mode.

(viii) *The mean vulnerability* was defined as the average magnitude of failure.

(ix) *The maximum vulnerability* equaled the largest magnitude of failure.

Nandalal and Bogardi (1996) used an array of quantity related PIs to evaluate the performance of a single water supply reservoir whose operating strategies were derived by optimization considering both the quantity and quality of reservoir releases. Specifically, they adopted seven PIs to investigate the impact of different salinity reduction measures of reservoir releases on the quantitative aspects of the reservoir's performance:

(i) *The quantity-based reliability* depicted the total amount of delivered water relative to the total target release.

(ii) *The time-based reliability* was defined as the probability that the reservoir would be able to meet the full demand.

(iii) *The average interarrival time* described the average duration the system was continuously failing to provide the desired service.

(iv) *The average interevent time* depicted the average duration the system was managing to maintain full supply (i.e. the average time between two failure events).

(v) *The mean monthly deficit* measured the average magnitude of failures.

(vi) *The resilience* was defined as the longest duration of consecutive failure events.

(vii) *The maximum vulnerability* measured the magnitude of the most severe failure event.

A number of PIs is selected to compare different operating strategies of the case study system in this dissertation. The defined PIs do not depict the operating details of individual reservoirs. They rather describe the performance of the entire multiple-reservoir system with respect to the quantitative fulfillment of the water demand imposed upon the system (n.b. similar approach has also been adopted in Milutin and Bogardi 1995, 1996a and 1996b). The set of PIs used in this case study includes a number of criteria defined to evaluate various facets of reliability, resilience and vulnerability of the system's operation. A detailed definition of the adopted PIs is given in section 7.

Objective criteria

This section provides the detailed description of the three objective criteria used. Each of the three objective functions (i.e. supply quantity achievement, salinity threshold non-breach and reservoir storage target achievement) is presented in its full mathematical formulation. In addition, an introduction and an argumentation about the combined use of the objective functions in different optimization steps are given here as well.

Supply quantity objective

The supply quantity objective aims at minimizing the deviation of supply from the respective demand targets. The objective function is defined as an aggregate of the squared supply deviations from the respective demand targets over all individual demands and over the entire time span of the analyses:

$$Z_1 = \sum_{t=1}^{T}\sum_{i=1}^{N}(R_{ti} - D_{ti})^2 \tag{1}$$

where:

Z_1: supply quantity objective criterion achievement

T: number of time steps in the objective criterion assessment

N: number of demands

R_{ti}: allocation of supply to demand *i* in time step *t*

D_{ti}: demand *i* in time step *t*

To force the optimization procedure to seek the solution which is reducing the risk from extreme supply shortages, this objective is penalizing the supply deviation from its respective target as the square of the resulting deviation. If the objective function were linear, the optimization procedure would not make any distinction between, for example, a single large deficit and a number of smaller deficits amounting to the same total volume, which can clearly be deducted from an example presented in Table 1

Table1. An example of linear versus squared supply quantity objective function

Number of incidents	Individual deviations from the target (volume unit)	Aggregate linear deviation penalty (volume unit)	Aggregate squared deviation penalty [(volume unit)^2]
1	10	10	100
5	2, 2, 2, 2, 2	10	20
10	1, 1, 1, 1, 1, 1, 1, 1, 1, 1	10	10

By adopting such an objective function form, it is ensured that the optimization procedure will disregard, to the maximum extent possible, solutions which result in excessive supply shortages or surpluses. This approach therefore strives to reduce the vulnerability of the system performance.

Supply salinity objective

In essence, the initial assumptions used to define this objective function have been very similar to the ones used in the definition of the other two objectives. That is, given a certain salinity threshold beyond which the salinity of supply to a demand centre should not occur, this objective function should represent a penalty if such a case does happen. There are two principal differences between the supply salinity threshold objective and the other two objective functions:

(i) Supply salinity objective penalizes only the surplus of salt concentration beyond the specified threshold value, whereas the other two penalize the deviation from their respective target.

(ii) The units and the magnitude of surplus of salinity differ significantly from those in the other two objectives.

The first difference is no obstacle for the definition of the objective function. However, the second one does require careful consideration when defining the objective function. This is due to the fact that the intrinsic multiobjective decision making problem is to be transformed into a single (composite) objective optimization, thus requiring that different objective function components be additive (i.e. supply quantity achievement and salinity threshold non-breach objectives).

Since the objective functions should be used jointly in optimization, the second obstacle is overcome by redefining the supply salinity surplus formulation into a volumetric equivalent (volume of water) describing the relationship between the supplied volume and salinity, and the imposed supply salinity threshold. Namely, let the following be the variables and relations describing the aforementioned quantities:

(i) Salt concentration of the allocated supply to a demand centre (C_{ti}):

$$C_{ti} = \sum_{j=1}^{M} r_{tij} c_{tj} \bigg/ \sum_{j=1}^{M} r_{tij} \tag{2}$$

(ii) The total amount of water allocated (R_{ti}) to meet the demanded volume D_{ti}

$$R_{ti} = \sum_{j=1}^{M} r_{tij} \tag{3}$$

where the newly introduced symbols so far are:

r_{tij}: volume released from reservoir *j* for demand *i* in time step *t*

c_{tj}: salinity of release from reservoir *j* in time step *t*

If the salinity of the supply C_{ti} is beyond the maximum threshold salinity $C_{i\max}$ for that particular demand, one can assume that the supplied volume will have to be additionally treated or partially replaced by some fresh water amount (volume A_{ti} of salinity c_{ext}) which would then reduce the salinity of the originally supplied water to the threshold level, or lower. This amount of additional fresh water can be estimated from the salt balance inequality:

$$R_{ti} \cdot C_{i\max} \geq \left(R_{ti} - A_{ti}\right) \cdot C_{ti} + A_{ti} \cdot c_{ext} \tag{4}$$

or, expressed as the equality for estimating the minimum value of the volume A_{ti}:

$$A_{ti} = \begin{cases} R_{ti} \dfrac{C_{i\max} - C_{ti}}{c_{ext} - C_{ti}} & , \quad C_{ti} > C_{i\max} \\ 0 & , \quad otherwise \end{cases} \tag{5}$$

It need not be mentioned that the assumed salinity c_{ext} of this "external" source of fresh water must be lower than the supply salinity threshold $C_{i\max}$ of the demand in question.

Given the estimates of the required external source supply A_{ti} to dilute the allocated volumes in each time step when the supply salinity threshold breach occurs, the objective function value can be estimated as:

$$Z_2 = \sum_{t=1}^{T} \sum_{i=1}^{N} A_{ti}^2 \tag{6}$$

The objective is penalizing the volumetric equivalent of the supply salinity surplus beyond its respective threshold as the square of the equivalent volume of fresh water needed to dilute the allocated salinity to the respective threshold value. Again, the choice of a squared rather than linear form of the penalty is forcing the optimization procedure to opt for more failures of lesser magnitude rather than just a few of high ones (the principle of the example presented in Table1 is illustrative for this objective function as well.)

Reservoir storage target objective

The reservoir storage target objective function is very similar in its form to the supply quantity objective described before. Namely, it penalizes the deviation of the final storage volume of a reservoir observed in optimization/simulation from the respective target storage volume. The function itself is defined as an aggregate of the squared final storage volume deviations from their respective targets over all individual reservoirs and over the entire time span of the analyses:

$$Z_3 = \sum_{t=1}^{T}\sum_{j=1}^{M}\left(SF_{tj} - ST_{tj}\right)^2 \quad (7)$$

where the newly introduced symbols so far are:

Z_3: reservoir storage target objective criterion achievement

M: number of reservoirs

SF_{tj}: observed final storage volume of reservoir *j* in time step *t*

ST_{tj}: target final storage volume of reservoir *j* in time step *t*

Similarly to the discussion on the other two objective functions presented in the above sections, the storage target objective function is also defined as an aggregate of squared deviations to force the optimization procedure to avoid solutions with fewer high deviations as opposed to those with numerous lower deviations from the target (the example, which is not presented here, would resemble the one given in Table1).

Composite objective within resource allocation optimization

A genetic algorithm search for the best resource allocation pattern is based on the objective which minimizes the value of a so-called fitness function. In essence, a genetic algorithm fitness function is the equivalent of an objective function in an optimization procedure. The adopted fitness function is defined as an aggregate of two distinct components:

(i) Quantity related squared deviation of supply from the target demand, multiplied by the respective weight factor.

(ii) Salinity related squared penalty of a volumetric equivalent of the violation of the maximum acceptable supply salinity, multiplied by the respective weight factor.

Given the definition of the two individual objective functions Z_1 and Z_2, it is necessary to adjust their estimation for the purpose of their combined use in the aforementioned fitness evaluation. It should also be noted here that in the definition of the genetic algorithm's fitness evaluation model the allocated consumptive release cannot exceed the respective demand. Therefore supply shortage is the only possible quantitative supply failure, and surplus can never occur.

The penalty associated with a failure of meeting the quantity and/or quality requirement is derived under the assumption that either of the two is to be compensated for from an imaginary external source with water of a constant (low and known) salt concentration. The joint penalty for utilization of such a source is proportional to the square of the amount of water withdrawn regardless of the purpose of such a withdrawal (i.e. to compensate for quantity shortage or to improve the quality of delivered water or both). The penalty is thus estimated in four steps described below.

Step 1

Based on the observed quantitative supply deficit associated with a demand during a certain time step, the imaginary external source provides full compensation for the incurred shortage. The external compensation for the supply deficit affects the salt concentration of the water delivered to the demand centre. The estimation of the resulting salinity of the assumed "full supply" is computed from the following equations:

Salinity of the original supply from the associated reservoirs:

$$C_{ti} = \sum_{j=1}^{M} r_{tij} c_{tj} \Big/ \sum_{j=1}^{M} r_{tij} \quad (8)$$

Total volume supplied by the associated reservoirs:

$$R_{ti} = \sum_{j=1}^{M} r_{tij} \tag{9}$$

Salinity of "full supply" (including the volume provided by the external source):

$$C_{ti}^{'} = \frac{R_{ti} \cdot C_{ti} + \left(D_{ti} - R_{ti}\right) \cdot c_{ext}}{D_{ti}} \tag{10}$$

Salinity of "full supply" (in a slightly different form):

$$C_{ti}^{'} = \frac{R_{ti}}{D_{ti}} \cdot C_{ti} + \left(1 - \frac{R_{ti}}{D_{ti}}\right) \cdot c_{ext} \tag{11}$$

Step 2

Having estimated the salinity of the "full supply" after the initial compensation from the external source for the quantitative shortage, it is necessary to assess whether the newly obtained supply salinity is below the supply salinity threshold associated with this demand:

The "full supply" salinity is below the threshold value,

$$C_{ti}^{'} \leq C_{i\max} \tag{12}$$

and there is no need for additional fresh water supply, i.e. $A_{ti} = 0$.

The "full supply" salinity is still higher than the threshold value,

$$C_{ti}^{'} > C_{i\max} \tag{13}$$

and the additional fresh water volume (A_{ti}) is estimated from the salt balance equation for this demand (it needs no mention that $C_{ext} < C_{i\max}$)

$$D_{ti} \cdot C_{i\max} = \left(D_{ti} - A_{ti}\right) \cdot C_{ti}^{'} + A_{ti} \cdot c_{ext} \tag{14}$$

which leads to

$$A_{ti} = D_{ti} \cdot \frac{C_{ti}^{'} - C_{i\max}}{C_{ti}^{'} - c_{ext}} \tag{15}$$

Step 3

The total penalty f_{ti} (both quantity and salinity related) associated with the supply to this demand centre during one time step then becomes (w_q and w_s are penalty weights associated with the quantity and quality penalty components respectively):

$$f_{ti} = w_q \cdot \left(R_{ti} - D_{ti}\right)^2 + w_s \cdot A_{ti}^2 \tag{16}$$

where

$$w_q \geq 0 \tag{17}$$

$$w_s \geq 0 \tag{18}$$

$$w_q + w_s = 1.0 \tag{19}$$

Step 4

Summing up these individual penalties over all demand centres and over the entire period under consideration gives the total penalty associated with the system for the chosen release distribution pattern:

$$f = w_q \sum_{t=1}^{T} \sum_{i=1}^{N} \left(R_{ti} - D_{ti} \right)^2 + w_s \sum_{t=1}^{T} \sum_{i=1}^{N} A_{ti}^2 \tag{20}$$

The volume $(R_{ti} - D_{ti})$ in the above equation is the penalty base associated with the quantitative supply shortage whereas the amount of water A_{ti} represents the penalty base for the inadequate salinity of the delivered water.

Since genetic algorithms are essentially maximization search procedures, the presented penalty function must be transformed into an equivalent whose maximum will refer to the optimum solution of the allocation problem. In this case, the choice of transformation is rather simple. Namely, the actual fitness (objective) function f^* used is computed as the difference between the maximum possible penalty f_{max} estimated on the basis of equation (20) and the actual penalty f for a particular alternative solution [equation (20)]):

$$f^* = f_{max} - f \tag{21}$$

where f_{max} is estimated assuming the following:

(i) Weight factors w_q and w_s are set to 1.0 and 0.0, respectively.

(ii) Demands supplied by a single reservoir only encounter 100% deficit (no supply).

(iii) Demands supplied by multiple reservoirs receive full demand supply from each of the reservoirs (maximum surplus). It should be noted here that such a case is actually not possible within the settings of the genetic algorithm model. Nevertheless, it does ensure that the maximum possible fitness be certainly beyond any penalty value that can be encountered in the search.

Composite objective within operating policy optimization

The operating policy optimization is carried out using stochastic dynamic programming (SDP). The SDP model applies reservoir system decomposition and optimizes the operating policies of individual reservoirs in an iterative fashion. Therefore, the objective function does not reflect the objective achievement of the entire system like the allocation optimization model of the previous section, but only a contribution of a single reservoir operation to the overall objective function value. The adopted objective function is the sum of two components:

(i) The annual aggregate of the squared monthly deviation of release from the respective demand, multiplied by a given weight factor.

(ii) The annual aggregate of the squared deviation of monthly final storage volume from the respective target storage volume, multiplied by a given weight factor.

Since this model applies stochastic dynamic programming, the objective function value represents the expectation of the objective achievement covering the span of one annual cycle.

Unlike the combination of supply deficit and supply salinity objectives (Section 5.4), this compound objective function does not require transformation of either of its components since both represent volumetric quantities of the same type:

$$G = w_d \cdot \sum_{t=1}^{T} \left(R_{tj} - D_{tj} \right)^2 + w_v \cdot \sum_{t=1}^{T} \left(SF_{tj} - ST_{tj} \right)^2 \tag{22}$$

where the newly introduced symbols so far are:

w_d: weight factor for supply deviation component ($w_d \geq 0$)

w_v: weight factor for storage target deviation component ($w_v \geq 0$)

R_{tj}: total consumptive release of reservoir *j* in time step *t*

D_{tj}: total demand imposed upon reservoir *j* in time step *t*

Suffice it to say at this stage that both weight factors are predefined positive real numbers and must meet the condition:

$$w_d + w_v = 1.0 \tag{23}$$

Performance indicators

This section gives a full description of the risk and reliability indicators, hereafter referred to as performance indicators (PI), used in the present work. Performance Indicators (PIs) provide specific information about the performance of a system with regard to, for instance, the likelihood of the occurrence of insufficient supply, the probable severity of such a failure and the estimate of the likely duration of periods of full and insufficient supply, respectively. Since there are three objective criteria, the description distinguishes which indicators are appropriate for use in which of the objective cases. Furthermore, and due to the complexity of the system being analyzed, the estimation of performance indicators can be applied either to the system as a whole, to individual reservoirs or groups thereof, or to individual/groups of demand centres. The ultimate choice among the aforementioned alternatives is made during the analyses and is addressed accordingly.

Definitions

Since there are three distinct objective criteria considered it is deemed appropriate to introduce a few important terms at this stage to ensure that consistent terminology is used throughout the text:

(i) *Level of service.* The term "level of service" describes the extent to which a "service provider" (i.e. reservoir, reservoir system) fulfils its obligations towards meeting the agreed requirements of its "client(s)" (i.e. demand centres) during a single time step.

(ii) *Failure vs success.* Contrary to a "success" event, a "failure" event indicates that a "service provider" has not managed to provide the full service to meet the requirement of its "client(s)" during a certain time step (e.g. supply shortage occurred, maximum acceptable salinity of supply surpassed, storage target not achieved).

(iii) *Quantity-based performance indicators.* This set of PIs evaluate the performance of the selected system (i.e. single reservoir, system of reservoirs, single or group of demands) from the level of service point of view (i.e. supply quantity, supply salinity, storage target). Thus, the performance is assessed reflecting the magnitude of failure events and not their temporal distribution.

(iv) *Time-based performance indicators.* Contrary to quantity-based PIs, time-based indicators describe the temporal facets of failure and success event occurrence related to the level of service of the selected system (i.e. single reservoir, system of reservoirs, single or group of demands).

Quantity-based performance indicators

(i) *Quantity-based reliability* (PI_1), is a simulation-based estimate of the mean level of service delivery over the entire period under consideration:

$$PI_1 = \frac{\sum_{i=1}^{N_t} \max(0, T_i - S_i)}{\sum_{i=1}^{N_t} T_i} \qquad \text{(failure: shortage) (24)}$$

(ii) *Average magnitude of failure* (PI_3) is the simulation-based estimate of the mean magnitude of failure:

$$PI_3 = \frac{\sum_{i=1}^{N_t} \max(0, T_i - S_i)}{N_t} \qquad \text{(failure: shortage) (25)}$$

$$PI_3 = \frac{\sum_{i=1}^{N_t} \max(0, S_i - T_i)}{N_t} \qquad \text{(failure: surplus) (26)}$$

$$PI_3 = \frac{\sum_{i=1}^{N_t} (T_i - S_i)}{N_t} \qquad \text{(failure: desviation) (27)}$$

(iii) *(Undershooting) vulnerability* (PI_5) indicates the magnitude of the most severe failure, i.e. shortage failure type, observed over the entire simulation period:

$$PI_5 = \max_i [\max(0, T_i - S_i)] \qquad \text{(failure: shortage) (28)}$$

(iv) *(Overshooting) vulnerability* (PI_6) indicates the magnitude of the most severe failure, i.e. surplus failure type, observed over the entire simulation period:

$$PI_6 = \max_i [\max(0, S_i - T_i)] \qquad \text{(failure: surplus) (29)}$$

Time-based performance indicators

(v) *Time-based reliability* (PI_7) is the simulation-based estimate of the long-term probability that the system service will be able to meet the target (consequently, the likelihood that the system will fail to provide the targeted service is 1 - PI_7):

$$PI_7 = 1 - \frac{1}{N_t} \sum_{i=1}^{N_t} u_i \qquad (30)$$

(vi) *Average (success) recovery time* (PI_8) is defined as the average number of successive time steps the system continuously fails to meet the target, thus stating the expected time required by the system to switch to an operating mode characterized by full service delivery once it has encountered an operating service failure during one time step (this PI can thus be described as the *average duration of failure*):

$$PI_8 = \frac{\sum_{i=1}^{N_t} u_i}{\sum_{i=1}^{N_t} v_i} \qquad (31)$$

(vii) *Average (failure) recurrence time* (PI_9) is defined as the average number of successive time steps the system sustains full service delivery before switching to a failure operating mode. In other words, it gives the estimate on how long the system may be expected to provide full service once it has recovered from an operating failure (this PI can thus be described as the *average duration of success, or full service*):

$$PI_9 = \frac{N_t - \sum_{i=1}^{N_t} u_i}{\sum_{i=1}^{N_t} w_i} \qquad (32)$$

(viii) *Resilience (or failure persistence)* (PI_{10}) is the longest interval *Di* (in number of time steps) of consecutive operating failure events:

$$PI_{10} = \max_{i}\left(\Delta i \mid v_i = 1 \wedge w_{i+\Delta i} = 1, \Delta i \geq 0 \wedge u_j = 1\ \forall j \in \{i+1,...,i+\Delta i - 1\}\right) \quad (33)$$

(ix) *Resistance (or success persistence)* (PI_{11}) is the longest interval *Di* (in number of time steps) of consecutive full operating service:

$$PI_{11} = \max_{i}\left(\Delta i \mid w_i = 1 \wedge v_{i+\Delta i} = 1, \Delta i \geq 0 \wedge u_j = 0\ \forall j \in \{i+1,...,i+\Delta i - 1\}\right) \quad (34)$$

The notation used in equations above is described in the following:

I: the index depicting a time step (i.e. month);

N_t: the length, in time steps (i.e. months), of the simulation time period;

N_y: the length, in years, of the simulation time period;

T_i: the target that the system service is expected to reach in time step *i*;

S_i: the service that the system is expected to provide in time step *i*;

$\sum_{i=1}^{12} T_{ij}$: the annual target that the system service is expected to reach in year *j*;

$\sum_{i=1}^{12} S_{ij}$: the annual service that the system is expected to provide in year *j*;

u_i: the *success/failure* (u_i=0/u_i=1) descriptor which indicates whether the system has managed to provide the expected service during time step *i*:

$$u_i = \begin{cases} 1, & T_i > S_i \\ 0, & T_i \leq S_i \end{cases}, \quad \forall i \qquad \text{(failure: shortage) (35)}$$

$$u_i = \begin{cases} 0, & T_i \geq S_i \\ 1, & T_i < S_i \end{cases}, \quad \forall i \qquad \text{(failure: surplus) (36)}$$

$$u_i = \begin{cases} 0, & T_i = S_i \\ 1, & T_i \neq S_i \end{cases}, \quad \forall i \qquad \text{(failure: desviation) (37)}$$

v_i: the descriptor indicating a *success-to-failure* operating transition:

$$v_i = \begin{cases} 1, & u_{i-1} = 0 \wedge u_i = 1 \\ 0, & otherwise \end{cases}, \quad \forall i > 1, \quad v_1 = u_1 \quad (38)$$

w_i: the descriptor indicating a *failure-to-success* operating transition:

$$w_i = \begin{cases} 1, & u_{i-1} = 1 \wedge u_i = 0 \\ 0, & otherwise \end{cases}, \quad \forall i > 1, \quad w_1 = 1 - u_1 \quad (39)$$

It should be noted here that the definitions and functional relationships of all the PIs have been presented assuming that the system's operation is characterized by both success and failure events thus excluding a possibility of a division by zero in the estimation of any of the PIs. Similarly, it is assumed that the target service imposed upon the system over the whole simulation span, as well as the length of the simulation period, are not zero.

To conclude, Table 2 summarizes the applicability of individual PIs to the assessment of system performance with regard to each of the three objective criteria.

Table 2. Summary on performance indicator applicability

	Objective		
Performance indicator	Supply quantity	Supply quality	Storage target
Quantity-based			
1. Reliability	✓		
2. Shortage index	✓		
3. Average magnitude of failure	✓	✓	✓
4. Average absolute magnitude of failure			✓
5. (Undershooting) vulnerability	✓		✓
6. (Overshooting) vulnerability		✓	✓
Time-based			
7. Reliability	✓	✓	✓
8. Average (failure) recurrence time	✓	✓	✓
9. Average (success) recovery time	✓	✓	✓
10. Resilience (or failure persistence)	✓	✓	✓
11. Resistance (or success persistence)	✓	✓	✓

Methods and Models

The adopted operations research methodology for the analysis of a multiple-reservoir system operation is based on the operating problem decomposition. In other words, a complex optimization problem is split into a series of simpler problems, which are subsequently solved individually with due consideration of extraneous variables created by problem decomposition. The adopted approach combines the decomposition of the original problem into two components, i.e. derivation of reservoir-demand allocation patterns and optimization of individual reservoir operating policies, with a physical decomposition of the system into individual reservoir subsystems (N.B. the approach flowchart is given in Fig. 1). The solution to the first sub-problem is obtained by a genetic algorithm (GA) search whereas the second sub-problem is solved by a stochastic dynamic programming (SDP) optimization. Both approaches, however, make use of system decomposition into single reservoir subsystems, simulation and hierarchical release allocation among each reservoir's water users.

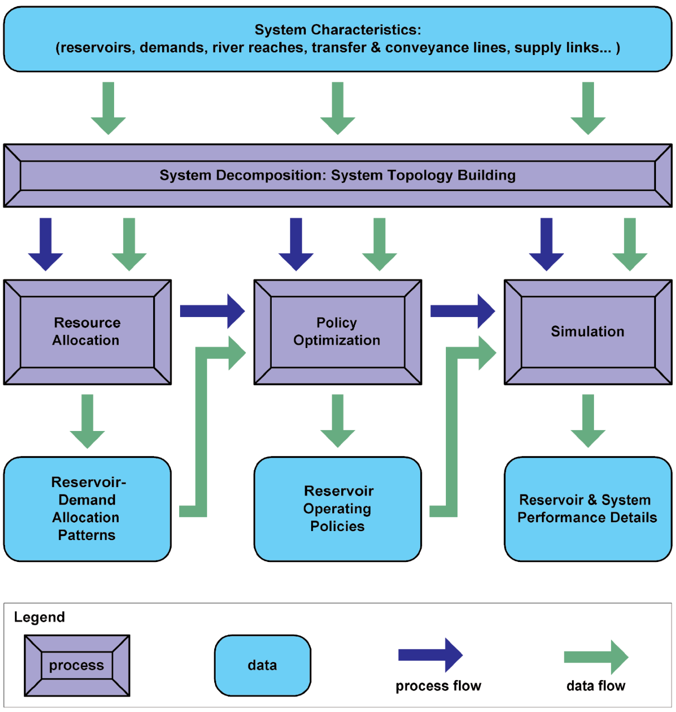

Fig.1. The adopted approach for system operation optimization.