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Abstract

One of the challenges facing water managers is how to supply various downstream claims with conflicting priorities, especially during drought conditions. This study calculates the total volumes of water released from the Shahid reservoir in the Fars province, Iran, during a five-year drought period using a standard operation policy (SOP) and genetic programming (GP). The calculated releases with these two methods show the vulnerability index (Vul_{Max}) equals 87 and 82 %, the time-based reliability index is 45 and 42 %, and the resiliency index reaches 23 and 13 % for the SOP and GP, respectively, whereas the volumetric reliability index equals 55 % for both methods, demonstrating superior results for the GP method. The releases calculated with SOP and GP are allocated to meet downstream water demands according to their supply priorities. The proportional (Pro) method is used for this purpose considering the available reservoir water is less than the sum of demands. Compliance with the priority of supplying demands is approached with Nonlinear Programming (NLP) in the Pro method. The vulnerability index Vul_{Max} of allocated releases obtained with GP for urban, environmental, industrial, and agricultural demands equals 5, 50, 60, and 100 %, respectively. Our results show that using the Pro method under water-scarcity conditions with optimized release factors is effective in allocating water resources to meet downstream demands that have conflicting water-supply priorities.

Keywords: Reservoir operation; SOP; GP; Performance criteria; Bankruptcy; Pro method

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Introduction

The available water resources in a catchment are allocated to meet various functions such as municipal and industrial, agricultural, and environmental. Ever increasing populations, agricultural water use, and water needs for environmental protection frequently create imbalances between water resources sources and water uses. Water resources management strives to restore and maintain a balance between water sources and water uses. Surface water, groundwater, desalinated seawater and brackish water, water conservation, water recycling, and water infrastructure serviceability are means available to water resources managers to optimize the water supply-water use relations (Loáiciga, 2015). The optimization of reservoir systems is a particularly important water-management tool for water supply and environmental uses (Fallah-Mehdipour et al., 2013a).

There are multiple functions of reservoirs such as flood control, environmental water releases to support instream habitats, recreation, and other functions which may render reservoir operation and management a complex problem. Generally, reservoir operation is accomplished in two different forms: long-term and real-time operation. Long-term operation relies on historical statistics and hydrologic time series, assuming that the past is a good clue to the future. Optimization methods can be applied to these data to determine operation curves over weekly, monthly or seasonal time periods. Real-time reservoir operation, on the other hand, are designed to track these long-term guidelines over shorter time horizons in daily or hourly time increments (Labadie 2004). These models enforce frequent update of water management to adjust to changing circumstances. They consider incoming runoff, the current state of reservoir storage, and water demands to be met in the near term to choose a suitable operation strategy. Real-time reservoir operation is dynamic in its implementation (Bolouri-Yazdeli et al., 2014).

Many types of reservoir operation rules were presented by Bower et al. (1962). They defined and analyzed hedging rules with mathematical functions. Revelle et al. (1969) introduced the linear decision rule (LDR) to design and operation of reservoir system. Loucks and Dorfman (1975) presented a LDR in which the release volume was related to reservoir storage volume and inflow volume. Klěmes (1977) reported hedging rules in reservoir design. Hashimoto et al. (1982) stated hedging rules for reservoir designing and operation and introduced indices of reliability, resiliency, and vulnerability. Perera and Conder (1998) proposed operation rules consisting of restriction rules, target storage curves, and rule curves for designing and operating water-supply systems. Neelakantan et al. (1999) reviewed several reservoir operation rules. Dynamic programming (DP) and stochastic dynamic programming (SDP) are two optimization methods that discretize the decision space and determine optimal solutions searching this space. There are several studies dealing with DP and SDP applications for reservoir operation (Stedinger et al. (1984), Mousavi et al. (2005), Bozorg-Haddad et al. (2011), Husain (2012) and Zhao et al. (2012)). DP can determine optimal solutions by discretizing the decision space, yet, it is hindered by the "curse of dimensionality", that is, the very large number of discretized states that must be evaluated in searching for an optimal solution. The calculation of operating rule curves is a water resources systems problem with a high dimensional space that causes the curse of dimension.

Evolutionary Algorithms (EAs) in general, and the Genetic Algorithm (GA, see Holland, 1975) in particular, have gained prominence in the optimization of reservoir operation rules. Genetic Programming (GP) is an EA based on the GA that can be applied to handle complex mathematical relations needed in the field of water resources. It has been applied to different water problems in the literature such as groundwater depth forecasting (Bierkens 1998; Shiri and KişI 2011), rainfall-runoff modeling (Cousin and Savic 1997; Savic et al. 1999; Babovic and Keijzer 2003), forecasting water demand (Zhou et al. 2000, 2002; Nasseri et al. 2011) and calculating reservoir operation rule curves (Fallah-Mehdipour et al. 2013; Li et al. 2014). GP can be applied to calculate reservoir operation rule curves without requiring preset optimal operation patterns. Fallah-Mehdipour et al. (2012 and 2013b) developed a reservoir operation rule curve based on GP. Fallah-Mehdipour et al. (2013a) calculated optimal operation rules for a reservoir-aquifer system with GP.

Growing water demands and scarce water sources may cause what we herein call a state of water resources bankruptcy. In such water systems it is not possible to supply the desired water demand to all water users. In view of the growing mismatch between water sources and water uses it is essential to develop fair rules with the aim of reducing stresses among stakeholders with the objective of establishing sustainable water-resources systems. The supply of water to stakeholders respecting priorities during water-shortage periods is especially important in this respect. This problem can either be tackled by using a multi-objective optimization method, which needs an objective function to be defined for every demand, or by applying bankruptcy methods where a weight is considered for each demand based on its priority that turns the problem into a single-objective optimization. The latter method simplifies the problem of defining multiple objective functions a choosing a solution from an optimal pareto.

Bankruptcy-handling rules are used in finance to determine creditors' shares when the available shares cannot meet their claims in whole. Similarly, water resources systems faced with (water) bankruptcy can implement fair water-allocation practices based on bankruptcy methods. Due to the difficulties and complexities in developing a unified concept of fairness several bankruptcy methods have been developed. O'Neil (1982), Aumann and Maschler (1985), and Dagan and Volij (1993) reviewed several common bankruptcy methods such as the proportional (Pro) rule, the adjusted proportional (AP) rule, constrained equal awards (CEA) rule, the constrained equal loss (CEL) rule, the Talmud (Tal) rule, and the Piniles' (Pin) rule. Applications of these methods in water resources research is limited but there are a few, such as those by Kampas and White (2003), Sheikhmohammadi and Madani (2008), Ansink and Weikard (2009), and Madani and Dinar (2011). Mianabadi et al. (2014) proposed a bankruptcy method to conflict resolution in water resources allocation. Their method was employed to allocate Euphrates river's water between Turkey, Iraq, and Syria, and they showed that the method is useful in resolving conflicts that are associated with multinational water allocation.

The purpose of this study is to develop water-supply rule curves to optimally allocate reservoir releases to meet competing downstream claims under drought conditions. For this purpose, the SOP and GP are applied to obtain total releases in each period of reservoir operation with the aim of supplying the total stakeholders' claims. Subsequently, the Pro method is implemented to allocate water releases. The releases are made in a state of water-resources system bankruptcy during shortage periods. The Pro method is a type of cooperative game theory (Zarezadeh et al., 2012). This work considers the priorities of water supply in meeting demands. The NLP method is applied to calculate deficit volumes that arise when attempting to meet water demands. The NLP method allocates water according to supply priorities when shortages occur.

Methods

The GP, SOP, performance criteria, and the Pro method are described in the following sections.

Reservoir system operation

Reservoir releases in reservoir operation problems are considered as a decision variable. A reservoir operation rule curve involves coefficients and functions that are considered as decision variables (Fallah-Mehdipour et al. 2012):

$$R_t = F(S_t, Q_t) \quad (1)$$

t = 1, 2, …., T; R_t = release volume during the t-th time period (MCM = millions of cubic meters = 10^6 m^3); S_t = storage volume at the beginning of the t-th time period (MCM); Q_t = inflow volume to the reservoir during each t-th time period (MCM); and F is a linear or nonlinear function obtained with GP.

There are several functions that can be considered as a rule curve, such as linear equations (Mousavi et al., 2007, and Bozorg-Haddad et al., 2008):

$$R_t = a \times S_t + b \times Q_t + c \quad t = 1, 2, …., T \quad (2)$$

in which a, b, and c are coefficients obtained by regression analysis of time series data. Bolouri-Yazdeli et al. (2014) used quadratic and cubic functions given by Equations (3) and (4), respectively, to operate reservoir systems:

$$R_t = a \times S_t^2 + b \times Q_t^2 + c \times S_t + d \times Q_t + e \quad (3)$$

$$R_t = a \times S_t^3 + b \times Q_t^3 + c \times S_t^2 + d \times Q_t^2 + e \times S_t + f \times Q_t + g \quad (4)$$

t = 1, 2, …., T, in which a, b, c, d, e, f, g are coefficients calculated by optimization. Equations (1)-(4) have predetermined structure. A better equation may exist with other type of mathematical relations without predetermined linear or nonlinear structure. Many efforts have been devoted for determining a suitable model of reservoir operation using a universal approximator such as neural networks (Giuliani et al. 2015). But accuracy of these methods is limited by the accumulation of the approximation error. It is possible also to construct the exact functional form from the data, that is, to obtain an estimate of the model by searching in a functional space (Varadan and Leung 2001). GP treats all the variables, mathematical operators and coefficient values as decision variables. A GP-developed rule is not bounded by a predefined set of rules. Thus, GP is capable of yielding more flexible rules which may help the operators to meet more targets. (Fallah-Mehdipour et al. 2012, 2013b). This study finds reservoir operation rule curves without predetermined structure by means of GP, and the results are compared with the SOP.

The objective function of reservoir operation herein entertained is the minimization of the sum of the relative deviations between release and demand volumes:

$$Minimize \ Z = \sum_{t=1}^{T} \left(\frac{D_t - R_t}{D_t} \right) \quad (5)$$

in which Z = objective function of supplying downstream demand; T = number of operation periods; and D_t = downstream demand during the t-th period (MCM).

The continuity (mass-balance) equation of reservoir operation is as follows:

$$S_{t+1} = S_t + Q_t - R_t - SP_t - Loss_t \quad (6)$$

t = 1, 2, …., T, in which S_{t+1} = reservoir storage volume at the beginning of the (t+1)-st time period (MCM); S_t = reservoir storage volume at the beginning of the t-th time period (MCM); Q_t = inflow volume during the t-th time period (MCM); SP_t = spill from reservoir during the t-th time period (MCM); and $Loss_t$ = reservoir losses during the t-th time period (MCM), losses due evaporation only. $Loss_t$ is calculated during each period with Equation (7):

$$Loss_t = EV_t \times \overline{A}_t \qquad (7)$$

t = 1, 2, …., T, in which $\overline{A}_t$ = average reservoir surface during the t-th time period (km^2) which is calculated by Equation (8); and EV_t = evaporation depth the during t-th time period (m).

$$\overline{A}_t = \left(\frac{A_t + A_{t+1}}{2}\right) \qquad (8)$$

in which A_t is expressed as a cubic function of S_t .

The R_t and S_t values are subject to constraints:

$$0 \le R_t \le D_t \qquad (9)$$

$$S_{Min} \le S_t \le S_{Max} \qquad (10)$$

t = 1, 2, …., T, where S_{Min} and S_{Max} are the minimum and maximum values of reservoir storage (MCM = 10^6 m^3), respectively.

Constraints (9) and (10) can be imposed to the reservoir optimization problem explicitly, or they can be added as penalty functions to the objective function. The penalty functions are written in Equations (11)-(14). They penalize the objective function whenever $S_t < S_{Min}$, $S_t > S_{max}$, $R_t <= D_t$ and $R_t < 0$, respectively.

$$PF1_t = A'.\left(\frac{|S_{Min} - S_t|}{S_{Max} - S_{Min}}\right)^2 + B' \qquad t = 1, 2, ..., T \qquad (11)$$

$$PF2_t = K'.\left(\frac{|S_t - S_{Max}|}{S_{Max} - S_{Min}}\right)^2 + D' \qquad t = 1, 2, ..., T \qquad (12)$$

$$PF3_t = P'.\left(\frac{|R_t - D_{Max}|}{D_{Max}}\right)^2 + F' \qquad t = 1, 2, ..., T \qquad (13)$$

$$PF4_t = G'.\left(\frac{|R_t|}{D_t}\right) + H' \qquad t = 1, 2, ..., T \qquad (14)$$

in which $PF1_t$, $PF2_t$, $PF3_t$ and $PF4_t$ = penalty functions and $A', B', K', D', P', F', G'$ and H' = constant positive coefficients of the penalty functions. The values of these constants are determined by a trial and error process, whereby the chosen constants reduce the objective function (under minimization) more than other values and cause faster convergence to a near-optimal solution.

Genetic programming (GP)

GP is a metaheuristic algorithm that searches the decision space randomly and calculates the values of the decision variables near optimal solutions. GP, just as the genetic algorithm (GA), implements an algorithm that mimics evolutionary natural phenomena with recursive calculations and logic. GP was introduced by Koza (1992, 1994) and Deb (2001).

GP is an artificial intelligence technique that can express complex problems using mathematical and logical relations. The search process and convergence to an optimal solution is similar to the GA, with the exception that the decision variables are not expressed exclusively in numerical form. They include operators, functions, and coefficients. This wide range of tools provides the GP with a wide-ranging capacity to express mathematical functions and relations. The GP algorithm begins with the generation of tentative random solutions that are metaphoric of real chromosomes. The chromosomes are evaluated by the objective function and then they are ranked. Populations of solutions are generated in each

search step of the optimization and are modified and improved randomly by crossover and mutation operators until convergence to a near-optimal solution is reached.
The GA and GP were coded in the software package Matlab7.0. A code consisting of mathematical operators (for example $\{\pm, \times, \div\}$) and various functions (for example $\{\sin, \cos, power\left(x^{y}\right), \sqrt{\ }\}$) is written to create a random relation between non-decision variables (inflow and storage volumes) and decision variables (release volumes R_t). This is the basis for calculating reservoir operation curves with GP. The release values are calculated with GP, and the corresponding values of the objective function [Equation (5)] are evaluated. In each iteration of GP a rule curve relation is generated, and the release (R_t) values and values of the objective function (Z) are calculated and ranked. The generation and evaluation actions are repeated in the next iteration resorting to mutation and crossover operators. The GP iterations continue until its search algorithm reaches a near-optimal solution. The optimization results consist of the operation rule curve and the calculated values of the objective function, storage, and spill volumes corresponding to the optimal releases. Figure 1 illustrates the GP framework for reservoir operation envisioned in this work.

The standard operation policy (SOP)
SOP is the simplest operation rule for reservoirs. According to the SOP the release volume from a reservoir depends on the demand volume in each period *t* (D_t). Equation (15) expresses the SOP:

$$R_t = \begin{cases} S_t + Q_t & if \quad S_t + Q_t \le D_t \\ D_t & if \quad D_t \le S_t + Q_t \le S_{\max} \\ S_t + Q_t - S_{\max} & if \quad S_t + Q_t - D_t > S_{\max} \end{cases} \qquad (15)$$

The SOP method does not consider future conditions surrounding reservoir management.

Reservoir performance criteria
The performance of water resources systems is assessed typically as Satisfactory or Unsatisfactory in many studies. Several indices are used to classify the performance of water recourse systems. The simplest system performance criterion is expressed in terms of the average and variance of releases from reservoirs. These criteria are useful, but they do not describe system performance accurately in the case of critical failures.
The analysis of reservoir system performance generally relies on the capacity of the system to achieve specific performance thresholds. Hashimoto et al. (1982) evaluated reservoir performance from three perspectives: (1) how frequently does the reservoir system fail?; (2) how quickly does the system return to a satisfactory situation after a failure?; and (3) how severe are the failures of the reservoir system? This study relies on three indexes, namely, reliability, resiliency, and vulnerability to assess the performance of a reservoir system.

Reliability
Reservoir systems are prone to failure by not meeting demands during drought periods. System failure during multiple operation periods is commonly analyzed using a reliability index. The reliability index has two definitions: (1) time-based reliability, and (2) volumetric reliability. Hashimoto et al. (1982) defined the time-based reliability as the probability of not having reservoir operation failures during operation periods. The volumetric reliability equals that ratio of the sum of releases to the sum of demands during the operation period. The time-

based and volumetric reliabilities are expressed mathematically by Equations (16) and (17), respectively:

$$\mathrm{Re}l_T = 1 - \frac{f}{T} \quad (16)$$

$$\mathrm{Re}l_V = \frac{\sum_{t=1}^{T} R_t}{\sum_{t=1}^{T} D_t} \quad (17)$$

in which $\mathrm{Re}l_T$ and $\mathrm{Re}l_V$ = time-based and volumetric reliability indices; respectively; f = the number of failure periods; and T = the number of operation periods.

Resiliency

This index represents the system after failure: it measures how quickly a reservoir system returns to a satisfactory condition. Hashimoto et al. (1982) defined resiliency as the probability of a system to return to a satisfactory state after incurring a failure. The resiliency index is calculated using Equation (18):

$$\mathrm{Re}s = \frac{f_s}{f} \quad (18)$$

in which $\mathrm{Re}s$ = resiliency index; f = the number of failure periods, and f_s = the number of series of failure periods. A series of failure periods has two or more consecutive failure periods.

Vulnerability

This index determines the severity (amount) of reservoir system failure. Among the series of failure periods of various lengths, that with the largest water shortage has the maximum effect on users. Hashimoto et al. (1982) defined the vulnerability index as the average of the maximum shortages that happen in the series of failure periods, and is calculated by Equation (19):

$$Vul = \frac{\sum_{k=1}^{f_s} Max(sh_k)}{f_s} \quad (19)$$

in which Vul = vulnerability index; and sh_k = maximum shortage during the k-th failure series. GP seeks to maximize the reliability and resiliency indexes, whereas it minimizes the vulnerability index.

Conflict resolution

Water resources stakeholders, or water users, vie for commonly shared water under scarcity giving rise to a competitive allocation problem. Game theory can play a useful role in the identification and interpretation of stakeholders' strategies in describing the interaction between them in water resources problems. Stakeholders (these are the players or water users in the case of water supply problems under scarcity) prioritize their own benefits when exploiting a commonly shared resource instead of prioritizing the benefit of the total system. Therefore the resource allocation results that are obtained with game theory are different from those obtained with traditional optimization methods, where the stakeholders' activities strive to improve the entire system (Madani, 2014). Several methods based on game theory such as Metagame analysis, Hypergame analysis, conflict analysis, graph model for conflict resolution (GMCR), drama theory, and the theory of moves have been proposed to model conflict resolution among water stakeholders (Madani, 2010). Game theory problems are often multi-criteria, multi-decision-maker, problems. These problems can be converted to single-decision-maker, conventional optimization, problems with a single composite objective function for a water resources system. The objective function can be an overall economic or social welfare function or a weighted constrained multi-objective function. Typically, perfect simultaneous cooperation among the decision makers is assumed to occur with the system's optimal solutions. The decision makers are assumed to contribute to optimizing the objective function without giving priority to their own objectives. However, in game theory each decision maker is part of the water-allocation game and seeks to optimize his own objective, knowing other players' decisions affect his objective value and that his decision affects others' payoffs and decisions (see Madani, 2010, and Loáiciga, 2004, for game-theoretic strategizing by groundwater users).

This study considers various conflicts that arise between water users (stakeholders) receiving releases downstream of a reservoir, and applies game theory to allocate water resources to the stakeholders.

Proportional method (Pro) with improved coefficients

The allocation of water to stakeholders is complicated by conflicts, especially under drought conditions in water-scarce regions. The Pro is an efficient approach among the bankruptcy methods, and is applied in this work to allocate water to meet downstream demands. Let the available water (the same as the release volume) and the total water claim by stakeholders during *t*-th period be denoted by E_t and C_t, respectively. Under water-shortage conditions $E_t \leq C_t$, and the water shortage Y_t during period t is:

$$Y_t = C_t - E_t \tag{20}$$

The Pro method allocates water to stakeholders using Equations (21) and (22):

$$a_{i,t} = w_t \times c_{i,t} \tag{21}$$

$$w_t = \frac{E_t}{C_t} \tag{22}$$

in which $a_{i,t}$ = the water-allocation value to the *i*-th stakeholder during the *t*-th period; $c_{i,t}$ = the value of the claim to water of the *i*-th stakeholder during the *t*-th period; and w_t = the shortage fraction during the *t*-th period, and *i* = 1, 2, 3, 4 is the stakeholder index with 1, 2, 3, and 4 representing urban, environmental, industrial, and agricultural water uses, respectively.

This paper's method allocates water to meet downstream demands considering water-claim priorities. Therefore, the shortage fraction w_t depends on the nature of downstream demands. This paper applies the NLP method to calculate the shortage fraction for the *i*-th stakeholder during the *t*-th period as shown in Equations (23) through (29):

$$y_{i,t} = c_{i,t} \times \left(1 - w_{i,t}\right) \tag{23}$$

in which $y_{i,t}$ =shortage value for *i*-th stakeholder during the *t*-th period; and $w_{i,t}$ = the supply percentage of the *i*-th stakeholder during the *t*-th period, which is calculated by optimization (using NLP) by solving the optimization problem embodied by Equations (24)-(29):

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$$Minimize\ O = \sum_{t=1}^{T}\left(Y_t - \sum_{i=1}^{4} y_{i,t}\right)^2 \quad (24)$$

Subject to:

$$0.95 \le w_{1,t} \le 1 \quad (25)$$

$$0 \le w_{2,t} \le 1 \quad (26)$$

$$0 \le w_{3,t} \le 1 \quad (27)$$

$$0 \le w_{4,t} \le 1 \quad (28)$$

$$w_{4,t} \le w_{3,t} \le w_{2,t} \le w_{1,t} \quad (29)$$

in which O = optimization function; and $w_{1,t}$, $w_{2,t}$, $w_{3,t}$, $w_{4,t}$ = supply percentages for urban, environmental, industrial, and agricultural water uses, respectively. Equation (24) means that the total water allocation in each period may not exceed the available water while observing the existing allocation priorities. Equation (25) stipulates that the urban water allocation must not be less that 0.95 of its total demand. Constraints (26), (27), and (28) limit the supply percentages of environmental, industrial, and agricultural water users to be in the range [0, 1].

Case study

The method proposed in this study was used to develop an optimal operation of Shahid dam in the Fars province of Iran.

General characteristics

Shahid dam and its reservoir are located in the Kameh sub-basin, south of the town of Semirom. Minimum and maximum storage volumes of the Shahid dam are 6.3 and 140.6 MCM, respectively. Figure 2 is a schematic of the Shahid dam and its downstream demands. Average long-term inflow rate of the Marbor river equals 5.2 m^3/s. Inflow data corresponds to a time series from water years 1961-1962 through 2000-2001. Data from 1965-1966 through 2000-2001 were used to train the GP method and the first 5- year (drought) period was applied to test the rule curve generated with GP.

Results

Training (or calibration) of GP was done with 35 years of inflow data, and the GP code was run with different number of iterations (from 100 to 20,000), different number of search trees (from 5 to 50), depths of trees equal two and three, and a sensitivity analysis was carried out. The performance of the rule curve obtained by GP was evaluated by simulating reservoir operation over a five-year period and comparing its performance results with those of the SOP. The comparison indices are the value of the objective function for the testing period and the reservoir performance criteria. The optimal value of the objective function and the best rule curve were obtained by running the code with 700 iterations, the number of tree equals 40, and the depth of trees equals to two. The optimal values of objective function obtained with the release volumes calculated with GP for the training and testing periods were 50.56 and 19.3, respectively. The optimal objective function value obtained with the release volumes calculated with the SOP equals 24.4.

The reservoir performance criteria of the releases obtained with the SOP and GP are listed in Table 1. Except for the volumetric vulnerability index for which both the methods have the same values, other operation indices by GP are better than those obtained with the SOP.

Therefore, it is concluded that reservoir operation calculated with GP is superior to that those obtained with the SOP based on the chosen performance indices.

Figure 3 displays the contour chart of water release volume in function of reservoir inflow v and storage. Figures 4 (a)-(d) show the water stakeholders' claims calculated with SOP and GP and applying the Pro method. Release volumes calculated with the SOP and GP are portrayed, where it is seen that the GP's rule curve avoids severe failures in upcoming periods by applying shortages in each period. It is seen in these Figures that supplying the water demands of urban, environmental, industrial, and agricultural were reduced, and the reservoir-operation results fit well the defined water-supply priorities. In addition, there are significant shortages in supplying the agricultural demand because (i) in many operation periods the agricultural demand is the significant part of total demand volume, (ii) the operation period that was chosen to simulate reservoir operation is a drought period, and (iii) the priority of supplying the agricultural water demand is the lowest.

Table 2 lists the values of the performance criteria applied to the supply of downstream demands used for the SOP and GP. Table 2 shows that GP indices such as $\mathrm{Re}l_V$, and $\mathrm{Re}l_T$ for agricultural water supply are 21 to 29% lower (that is, better) than those associated with the SOP, and that the calculated Vul_{Max} was the same with the two methods. Yet, Vul was reduced (improved) 24%. The indices $\mathrm{Re}l_V$, $\mathrm{Re}l_T$, $\mathrm{Re}s$, and Vul_{Max} calculated with GP for industrial water supply were improved 24, 29, 80, and 25%, respectively, compared with the values calculated by the SOP. The indices $\mathrm{Re}l_V$, $\mathrm{Re}l_T$, $\mathrm{Re}s$, and Vul_{Max} calculated with GP to supply environmental demand were improved 17, 27, 117, and 29% compared with the corresponding values from the SOP. The indices $\mathrm{Re}l_V$, $\mathrm{Re}l_T$, $\mathrm{Re}s$, and Vul_{Max} for the urban demand with first priority calculated with GP were improved 4, 62, 285, and 67% compared with the SOP-calculated values. Concerning the supply of urban, environmental, industrial, and agricultural water demands, the values of the indices $\mathrm{Re}l_V$, $\mathrm{Re}l_T$, and $\mathrm{Re}s$ calculated by GP increased (that is, improved), and those for Vul, and Vul_{Max} decreased (that is, improved) relative to those calculated with the SOP. In summary, the priorities of supplying water demands were observed and an appropriate allocation to downstream water users was achieved with GP under drought conditions.

Concluding remarks

Optimal reservoir operation must take a comprehensive view of supplying current and future water demands. The proposed method for reservoir operation presented in this paper increases the number of water-shortage periods but reduces the intensity of shortages. Long-term reservoir operation associated with the SOP does not help operators improve releases in current and future periods significantly. Adaptive release rule curves calculated with GP are correlated to independent variables such as reservoir inflow during each operation period and to the storage volume at the beginning of each period. In addition to these advantages of the proposed method, its allocation of water resources to various water demands considering the priorities of water-supply alternatives resolves or diminishes conflicts among water users that tend to be exacerbated during water-shortage conditions. Reservoir operation was evaluated with the SOP and the GP method and their performance criteria were compared for a 5-year period. Vul_{Max} is a significant performance index whose SOP and GP-calculated values were respectively 0.87 and 0.82, which shows GP's better performance. The reservoir release volumes calculated with the SOP and GP were allocated to downstream water users by considering water-supply priorities. In most of the operation periods the available water was

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less than the sum of downstream demands, and the water resources system was faced with bankruptcy. The proportional (Pro) method was used to find optimal water allocations under these conditions. Consideration of water-supply priorities was implemented with Nonlinear Programming (NLP). This work's results have demonstrated that using the Pro method under water-shortage conditions with optimized factors is effective in allocating water resources to various competing downstream demands with different water-supply priorities.

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Notations

R_t	release volume
S_t	storage volume
Q_t	inflow volume to the reservoir
F	a linear or nonlinear function
a, b, c, d, e, f and g	coefficients
Z and O	objective function
T	number of operation periods
D_t	downstream demand
SP_t	spill from reservoir
$Loss_t$	reservoir losses
A_t	reservoir surface
$\overline{A}_t$	average reservoir surface
EV_t	evaporation depth
S_{Min}	minimum reservoir storage
S_{Max}	maximum reservoir storage
$PF1_t$, $PF2_t$, $PF3_t$ and $PF4_t$	penalty functions
A', B', K', D', P', F', G' and H'	constant positive coefficients of the penalty functions
$\mathrm{Re}l_T$ and $\mathrm{Re}l_V$	time-based and volumetric reliability indices
f	number of failure periods
f_s	number of series of failure periods
$\mathrm{Re}s$	resiliency index
Vul	vulnerability index
sh_k	maximum shortage
E_t	available water
C_t	total water claim by stakeholders
Y_t	water shortage
$a_{i,t}$	water-allocation value
$c_{i,t}$	value of the claim to water
w_t	shortage fraction
$w_{i,t}$	supply percentage
$y_{i,t}$	shortage value
$w_{1,t}$, $w_{2,t}$, $w_{3,t}$, $w_{4,t}$	supply percentages for urban, environmental, industrial, and agricultural water uses

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Table 1. Values of reservoir performance criteria for the releases obtained by SOP and GP

method	Vul_{Max}	Vul (10^6 m^3)	Res	Rel_V	Rel_T
GP	0.82	11.94	0.23	0.55	0.42
SOP	0.87	21.58	0.13	0.55	0.35

Table 2. Reservoir performance criteria for each claim calculated with SOP and GP

Performance indexes	urban		Environmental		industrial		agricultural	
	SOP	GP	SOP	GP	SOP	GP	SOP	GP
Rel_V	0.95	0.99	0.78	0.85	0.55	0.68	0.34	0.24
Rel_T	0.62	1.00	0.37	0.47	0.35	0.45	0.67	0.53
Res	0.26	1.00	0.13	0.28	0.15	0.27	0.25	0.25
Vul (10^6 m^3)	0.59	0.00	1.08	0.83	1.92	1.57	19.01	14.09
Vul_{Max}	0.15	0.05	0.7	0.5	0.8	0.6	1.00	1.00

Figure 1. GP framework for reservoir operation

Figure 2. Schematic of the Shahid dam

Figure 3. Contour chart of water release (in 10^6 m^3) in function of reservoir inflow and reservoir storage calculated with GP

Figure 4. Release volumes obtained by SOP and GP that are allocated to: (a) urban water demand, (b) environmental water demand, (c) industrial demand and (d) agricultural water demand

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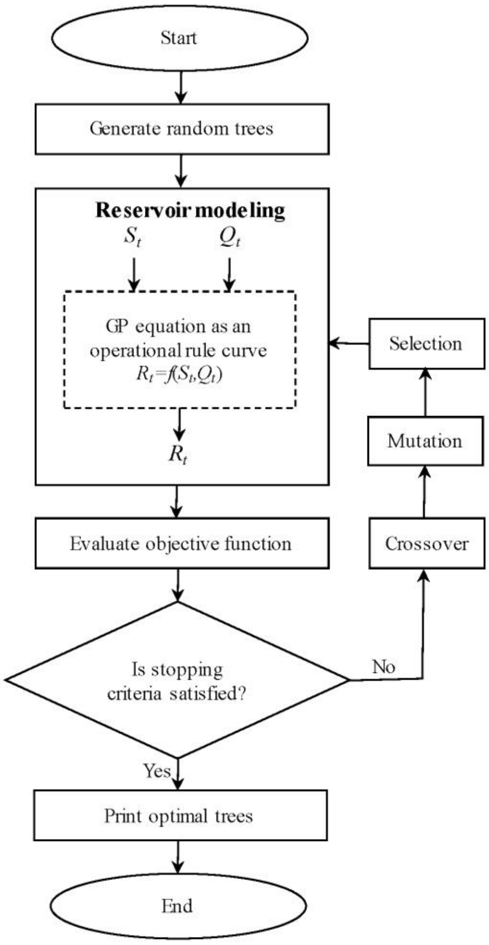

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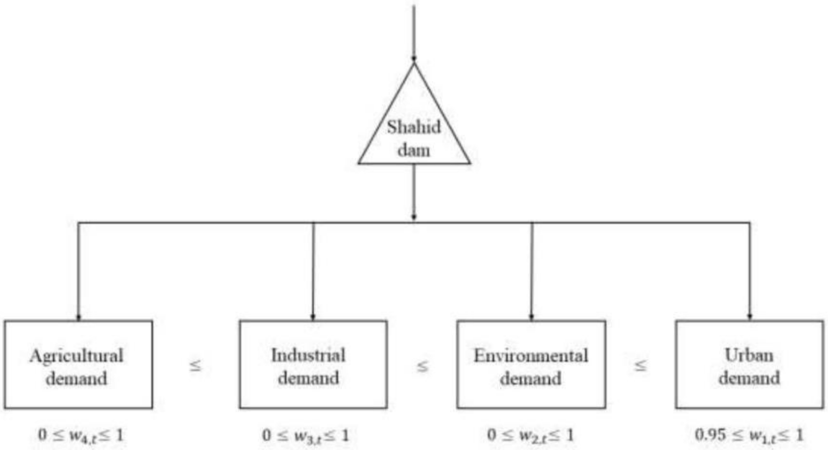

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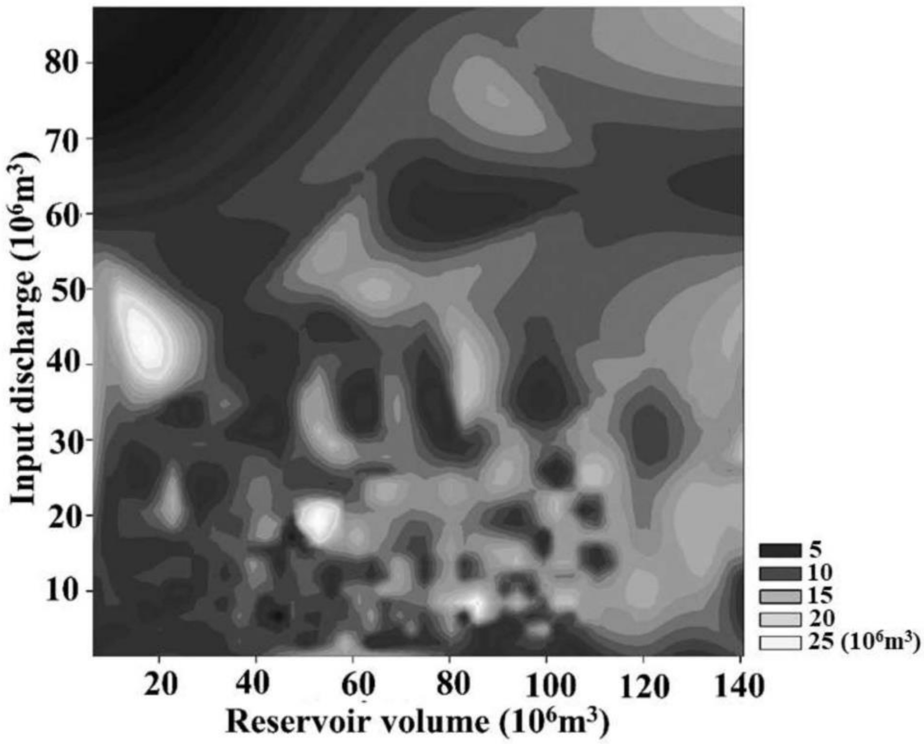

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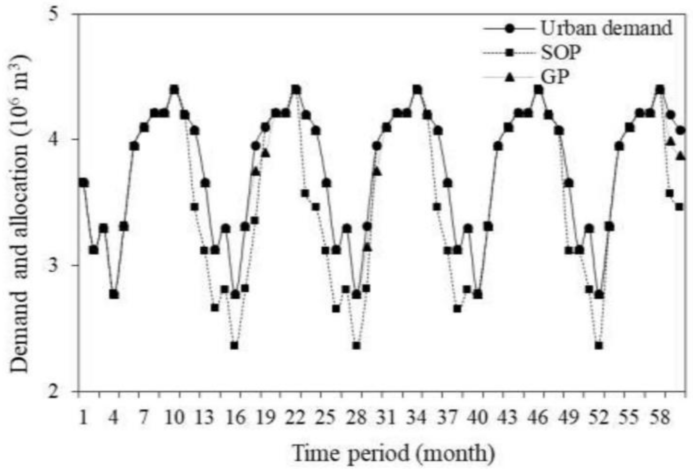

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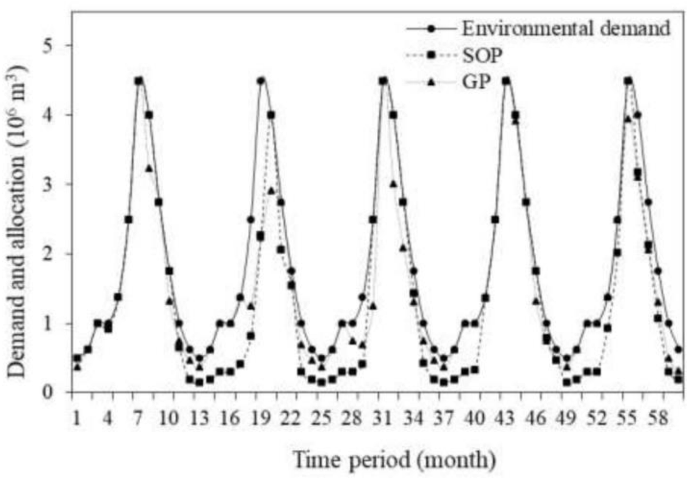

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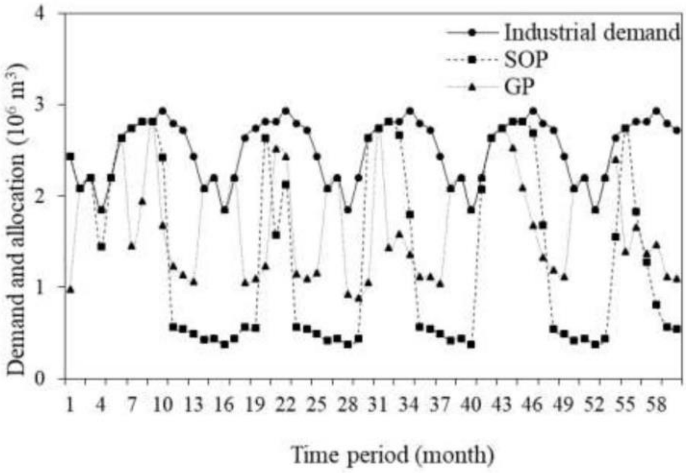

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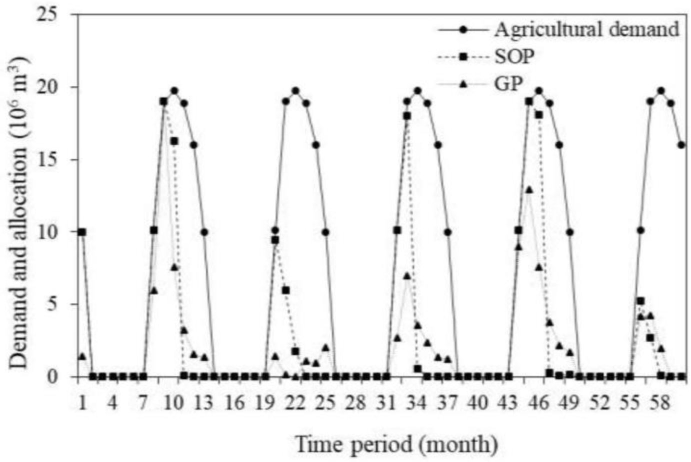

(d)

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