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Journal
Journal of Water Resources Planning and Management, 141(11)

ISSN
0733-9496

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Publication Date
2015-11-01

DOI
10.1061/(asce)wr.1943-5452.0000540

Evaluation of Climatic-Change Impacts on Multiobjective Reservoir Operation with Multiobjective Genetic Programming

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Abstract: Multiobjective genetic programming is used to calculate optimal reservoir-operating rules under baseline and climatic-change conditions. The rules are calculated based on river inflows to the Aidoghmoush Reservoir (located in East Azerbaijan, Iran), storage volume, and downstream irrigation demands. The objective functions are the maximization of the reliability of meeting irrigation demand and the minimization of the vulnerability to irrigation deficits in a baseline period (1987–2000) and a future period (2026–2039), the latter influenced by climatic change. The optimization results show that reservoir-operating rules that take into account changing climate would lead to improvements in reservoir performance on the order of 29–32% relative to operating rules based on baseline climatic conditions. **DOI:** 10.1061/(ASCE)WR.1943-5452.0000540.

Author keywords: Climatic change; Pareto curve; Multiobjective optimization; Reservoir operation; Irrigation.

Introduction

Most water-resources projects, such as reservoirs built to provide water for irrigation, were planned using reservoir-operation rules that correspond to historical conditions. Changing climatic conditions pose challenges to the performance of many water-resources systems that are currently operating under conditions that differ from those that existed when they were conceived decades ago. Climate change affects the planning, design, and operation of water projects, and therefore, a rational approach to future water management calls for the incorporation of climatic-change impacts in all aspects of water-resources management.

Recent publications dealing with optimization methods have covered several domains of water-resources systems, such as reservoir operation (Bozorg Haddad et al. 2011a, 2014; Fallah-Mehdipour et al. 2011b, 2012a, 2013a), levee layouts and design (Bozorg Haddad et al. 2015), hydrology (Orouji et al. 2013), project management (Bozorg Haddad et al. 2010a; Fallah-Mehdipour et al. 2012b), cultivation rules (Bozorg Haddad et al. 2009; Noory et al. 2012; Fallah-Mehdipour et al. 2013b), pumping scheduling (Bozorg Haddad et al. 2011b), hydraulic structures (Bozorg Haddad et al. 2010a), water-distribution networks (Bozorg Haddad et al. 2008; Fallah-Mehdipour et al. 2011a; Seifollahi-Aghmiuni et al. 2011, 2013), operation of aquifer systems (Bozorg Haddad and Mariæo 2011), site selection of infrastructures (Karimi-Hosseini et al. 2011), and algorithmic developments (Shokri et al. 2013).

Genetic programming (GP) and genetic algorithm (GA) are evolutionary algorithms that have been used by various researchers. Sivapragasam et al. (2008) investigated flood routing in natural channels using GP. Sivapragasam et al. (2009) modeled evaporation from two reservoirs in India using GP. Wang et al. (2009) compared the performance of several artificial intelligence methods for forecasting monthly discharge time series for two rivers. Khan and Tingsanchali (2009) developed a new model called reservoir optimization–simulation with sediment evacuation (ROSSE). The model applied GA-based optimization capabilities and embeds the sediment-transport module into the simulation module. In a study by Fallah-Mehdipour et al. (2012a), the GP was used to develop reservoir-operating policies simultaneously with inflow prediction. Khan et al. (2012) applied the ROSSE model with the aim of minimizing irrigation shortages in the Tarbela Reservoir, Pakistan. They calculated the suitable values of various GA parameters required to run the model through a sensitivity analysis. Fallah-Mehdipour et al. (2013c) investigated prediction and simulation of monthly groundwater levels with the GP. Other researchers have used the GP for issues related to water management. However, previous studies indicate that the GP has not been applied to solve multiobjective (MO) problems in the field of water-resources management.

Guo et al. (2007) introduced a hybrid cellular automaton and GA approach, called CAMOGA for MO design of urban water networks. Yang et al. (2007) used MO-GA to generate the various combinations of reservoir capacity and estimate the noninferior solution set. Consequently, the constrained differential dynamic programming (CDDP) was adopted to distribute optimal releases among reservoirs to satisfy water demand. Next, the effectiveness of the proposed methodology was verified by solving a MO planning problem of surface water in southern Taiwan. Redy and Kumar (2008) proposed the MO differential evolution approach for the determination of optimal cropping pattern. Yang et al. (2009) integrated the MO-GA, the CDDP, and the groundwater simulation model ISOQUAD to optimize reservoir releases and

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Note. This manuscript was submitted on July 27, 2014; approved on February 23, 2015; published online on June 8, 2015. Discussion period open until November 8, 2015; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Water Resources Planning and Management***, © ASCE, ISSN 0733-9496/04015030(9)/$25.00.

the conjunctive use of surface and subsurface water in southern Taiwan. Kang and Lansey (2010) developed a methodology that optimally located field-measurement sites and produced more reliable real-time state estimates of nodal demands. An optimal meter placement problem was solved using a MO-GA based on Pareto-optimal solutions. Mantoglou and Kourakos (2012) developed a methodology for the optimal remediation of groundwater aquifers using MO-GA and Pareto solutions. Rezapour Tabari and Soltani (2012) applied the nondominated sorting GA (NSGA-II) to maximize the reliability and minimize the costs of water supply. Shafiee et al. (2013) applied the MO Niching coevolutionary algorithm to design optimal water-supply networks and optimize water-quality-management problems. Leon et al. (2014) presented a dynamic framework for flood control in the Boise River system in Idaho. Their framework coupled a robust and numerically efficient hydraulic routing approach with NSGA-II. Li et al. (2015) developed a two-level linear fractional water-management model based on interactive fuzzy programming. The developed model could solve MO problems quantitatively, particularly for the ratio MO problems (e.g., benefit per unit of water in water-resources-management system).

Minville et al. (2009) investigated the operation of the PØribonka hydropower reservoir in Canada under climatic-change conditions. The Canadian regional climate model (CRCM) was nested within the third-generation Canadian-coupled global climate model forced with the A2 emission scenario, and the distributed hydrologic model HydroTel was coupled with the CRCM for hydrologic simulation. Raje and Mujumdar (2010) studied the performance of the Hirakud Reservoir, India, considering the uncertainty of hydrologic conditions due to climatic change. Eum et al. (2012) developed an integrated reservoir-management system for changing reservoir's existing operations under climate-change conditions. The reservoir-management system included (1) the *k*-nearest neighbor weather-generator model; (2) the Hydrologic Engineering Center-Hydrologic Modeling System hydrological model; and (3) the differential evolution optimization model. Ferreira and Taeegavarapu (2012) addressed the optimal operation of a multipurpose hydropower system under climatic change in Brazil. Results obtained using GA were superior relative to gradient-based methods. Georgakakos et al. (2012) compared adaptive reservoir management with traditional operation practices under climatic change in Northern California.

This paper develops and applies a novel MO optimization GP (MO-GP) algorithm to maximize the reliability index and minimize the reliability index of irrigation supply by the Aidoghmoush Reservoir system (East Azerbaijan, Iran). The MO-GP algorithm optimizes reservoir-operating rules for a baseline or historic period (1987–2000) and for a future period beset by climatic change (2026–2039).

Methodology

This section discusses methods used in this study that include the following: (1) climatic and hydrological processes for estimation of reservoir inflows and calculation of water-demand volumes in the baseline period (1987–2000) and under climatic-change conditions (period 2026–2039); (2) calculation of MO operating rules in the baseline period and under climatic-change conditions (based on inflows to reservoir, storage volume, and irrigation-demand volumes); and (3) comparison of optimal water-allocation policies in the baseline period and under climatic-change conditions. The main steps of this study's methodology are depicted in Fig. 1.

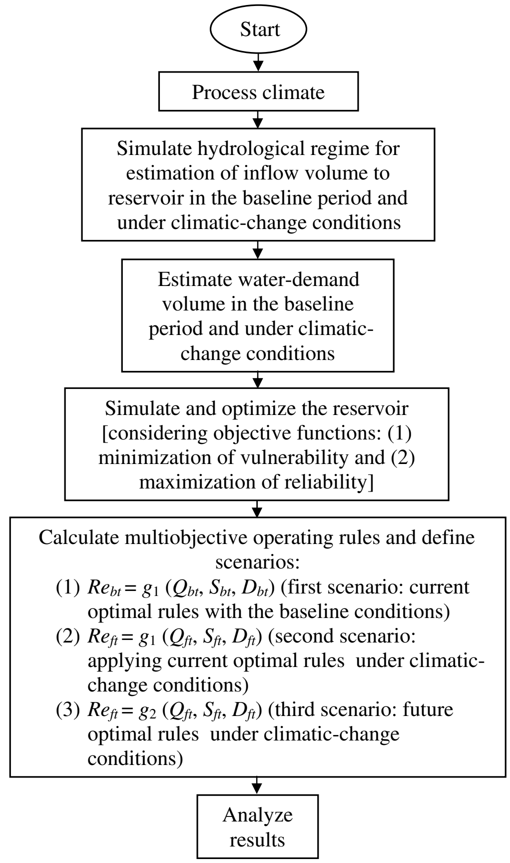

Fig. 1. Flowchart of the research methodology

Climatic-Input Downscaling and Hydrologic Modeling

Climate scenarios produced by the Hadley Centre coupled model, version 3 (HadCM3; Gordon et al. 2000) driven by the A2 greenhouse gases emission scenario (Intergovernmental Panel on Climate Change 2000) are used in this study [see Ashofteh et al. (2013a) for a background-related study]. A summary of the main consequences of the A2 emission scenarios are listed in Table 1 (Intergovernmental Panel on Climate Change 2000).

The perturbation-factor method is used in this work to downscale the HadCM3 climate outputs to the regional scale in the area of interest (Wilby and Harris 2006; Ashofteh et al. 2013b).

The identification of hydrographs and components from rainfall, evaporation and stream (IHACRES) hydrologic model (Jakeman and Hornberger 1993) is used to simulate inflow to the Aidoghmoush Reservoir in the baseline period and under climatic-change conditions. The main inputs to IHACRES are temperature and rainfall (in the baseline period and under climatic-change conditions), runoff parameters (for baseline conditions), and the basin area. The IHACRES model is used for rainfall-runoff simulation in this study under baseline and climatic-change conditions.

Table 1. Consequences of the A2 Emission Scenario in 2100

Data (unit)	Value
Population (10^9 people)	15.1
CO_2 concentration (ppmv)	834
Change of the average temperature of the Earth (°C)	3.1 (2.1–4.4)
Global sea-level rise (cm)	62 (27–107)
Global gross domestic product (10^{12} US$)	243

The Food and Agricultural Organization of the United Nations' (FAO) Irrigation and Drainage Paper 24 (FAO 24) (Doorenbos and Pruitt 1992) and the Penman–Monteith methods were used to determine crop and potential evapotranspiration, respectively (Ashofteh et al. 2013a).

Simulation and Optimization of Reservoir Operation

Reservoir simulation uses the continuity or mass-balance equation (the time steps are monthly)

$$S_{t+1} = S_t + Q_t - Re_t - (E_t \times \bar{A}_t) - Sp_t \quad t = 1, 2, \ldots, T \quad (1)$$

where S_t and S_{t+1} = storage volume of reservoir at the beginning and ending of period t, respectively; Q_t = inflow volume to reservoir during period t; Re_t = release volume of reservoir during period t; E_t = net evaporation depth (evaporation minus precipitation) in the reservoir during period t; $\bar{A}_t$ = average reservoir lake area in period t; and Sp_t = spill volume of reservoir during period t.

Area versus storage equation is given as follows:

$$\bar{A}_t = a_0 + a_1 \bar{S}_t \quad t = 1, 2, \ldots, T \quad (2)$$

where $\bar{S}_t$ = average reservoir storage calculated from the values at the beginning and end of period t; a_0 and a_1 = constants in the surface-volume equation.

Spill equation is given as follows:

$$Sp_t = S_t + Q_t - Re_t - E_t \times \bar{A}_t - S_{\max}$$
$$\text{if } S_t + Q_t - Re_t - E_t \times \bar{A}_t \geq S_{\max} \quad t = 1, 2, \ldots, T \quad (3)$$

$$Sp_t = 0 \quad \text{if } S_t + Q_t - Re_t - E_t \times \bar{A}_t < S_{\max} \quad t = 1, 2, \ldots, T \quad (4)$$

where $S_{\max}$ = maximum volume (capacity) of the reservoir.

There are two objectives in the reservoir-operation problem: the minimization of the vulnerability index (Ashofteh et al. 2015a; by not supplying the irrigation demand) and the maximization of the reliability index (Ashofteh et al. 2015a; resulting from supplying the irrigation demand) in the baseline period and under climatic-change conditions, as stated by Eqs. (5) and (6)

$$\text{Minimize } Fu_1 = \frac{\sum_{t=1}^{T} (D_t - Re_t | Re_t < D_t)}{\left[\overset{T}{\underset{t=1}{N}} (Re_t < D_t)\right] D_{\max}} \quad t = 1, 2, \ldots, T \quad (5)$$

$$\text{Maximize } Fu_2 = \frac{\overset{T}{\underset{t=1}{N}} (D_t - Re_t | Re_t \geq D_t)}{T} \quad t = 1, 2, \ldots, T \quad (6)$$

where Fu_1 = objective function of the vulnerability index; Fu_2 = objective function of the reliability index; D_t = irrigation-demand volume during period t; and $D_{\max}$ = maximum irrigation demand in the desired operating interval.

Constraints imposed on reservoir operation are given by Eqs. (7) and (8).

Constraint of minimum reservoir storage are as follows:

$$S_t \geq S_{\min} \quad t = 1, 2, \ldots, T \quad (7)$$

$$Re_t \geq 0 \quad t = 1, 2, \ldots, T \quad (8)$$

where $S_{\min}$ = minimum (dead) volume of reservoir.

Penalty values are added to the objective functions in case of constraints violations, as shown in Eqs. (9) and (10)

$$Fu_1 (\text{or } Fu_2) = Fu_1 (\text{or } Fu_2) \pm \left[A' \times \left(\frac{S_{\min} - S_t}{S_{\max} - S_{\min}}\right) + B'\right]$$
$$t = 1, 2, \ldots, T \quad (9)$$

$$Fu_1 (\text{or } Fu_2) = Fu_1 (\text{or } Fu_2) \pm \left[C' \times \left(\frac{Re_t}{D_{\max}}\right) + D'\right] \quad t = 1, 2, \ldots, T \quad (10)$$

where $[A' \times (S_{\min} - S_t / S_{\max} - S_{\min}) + B']$ = penalty value assessed to the violation of constraint (7); $[C' \times (Re_t / D_{\max}) + D']$ = penalty value assessed to the violation of constraint (8); and A', B', C', and D' = positive constants used in the penalty values.

Operating-Rule Curves and Scenarios under Consideration

The reservoir-operating rules are calculated with the objectives of (1) minimization of the vulnerability associated with demand deficits; and (2) maximization of the reliability of supplying irrigation demand using the MO-GP algorithm. The operating-rule formulas are listed in Eqs. (11)–(13)

$$Re_{bt} = g_1(Q_{bt}, S_{bt}, D_{bt}) \quad t = 1, 2, \ldots, T \quad (11)$$

$$Re_{ft} = g_1(Q_{ft}, S_{ft}, D_{ft}) \quad t = 1, 2, \ldots, T \quad (12)$$

$$Re_{ft} = g_2(Q_{ft}, S_{ft}, D_{ft}) \quad t = 1, 2, \ldots, T \quad (13)$$

where $g_1(Q_{bt}, S_{bt}, D_{bt})$ = first rule calculated with the MO-GP algorithm for the baseline period (1987–2000) under baseline conditions of reservoir inflow and irrigation demand (scenario 1); $g_1(Q_{ft}, S_{ft}, D_{ft})$ = second rule calculated with the MO-GP algorithm corresponding to the second scenario, that is, applying the reservoir-operating rules calculated for the baseline period (those of scenario 1) to the reservoir receiving future reservoir inflow and subjected to future irrigation demand (the future or climatic-change period is 2026–2039); $g_2(Q_{ft}, S_{ft}, D_{ft})$ = third rule calculated with the MO-GP algorithm associated with the third scenario, that is, applying the reservoir-operating rules calculated for the future period (2026–2039) using future reservoir inflow and demand; index bt = time index for the baseline interval; and index ft = time index for climate change interval.

MO-GP Algorithm

The objective functions used in MO problems commonly imply trade-offs. In the case of biobjective problems, this means that the improvement of one objective function can be achieved only at the expense of worsening the other. The goal of MO optimization is to achieve of a set of nondominated solutions (Pareto boundary or frontier), in which each combination of solutions on a Pareto boundary is valued equally by the decision maker.

The MO-GP algorithm, whose flowchart is depicted in Fig. 2, is a powerful algorithm for solving MO problems. In each computational time step, the algorithm considers the quality of solutions (their rank, which is the first factor) and the order of solutions (the dispersion of solutions, which is the second factor). The first stage of the MO-GP algorithm is the random production of initial populations of trees. Each decision tree consists of a set of functions and terminals that, with the structure of the tree itself, is considered as decision variables of the optimization model. Each tree is

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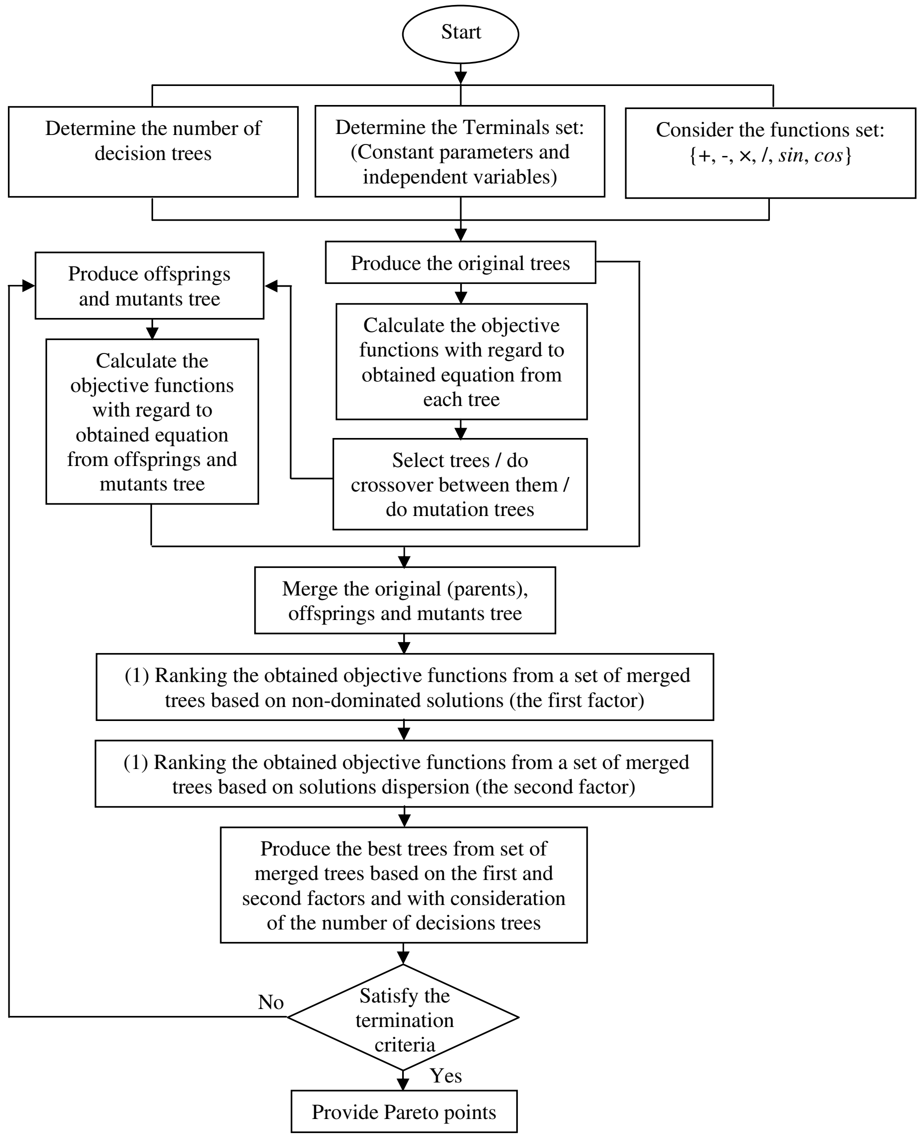

Fig. 2. Flowchart of the MO-GP algorithm

evaluated with the values of the objective functions. Then, the trees are grouped into different Pareto fronts based on nondominated ranking, considering the values of the objective functions. Next, trees ranked above low-ranking ones are selected, and the remaining trees are removed, so that the population size of initial trees in the next generation is similar to the population size of the initial trees in the previous generation. Trees are selected in the next generation among trees ranked atop of the population considering the second factor (i.e., the dispersion of solution), and the remaining decision trees are removed. After production of the initial population of trees, two trees are randomly selected and one of them is selected using a tournament method (considering factors one and two). The populations of offspring trees are generated by selection and crossover operators, and the populations of mutant trees are generated by a mutation operator. Then, the objective function values of offspring trees and mutant trees are recalculated. The three initial populations (parents, offsprings, and mutants) are merged and nondominated ranking is performed on the merged population. These steps are repeated until the stopping criterion is satisfied and the last generation is known as the Pareto boundary of Pareto solutions.

Aidoghmoush Reservoir and Its Downstream Area

The Aidoghmoush Reservoir serves an irrigation purpose. The MO-GP algorithm was applied to calculate operating rules for the Aidoghmoush one-reservoir system (northeastern Iran) and its downstream area of 13,500 ha [see description by Ashofteh et al. (2015b)]. The total capacity of the reservoir and its dead volume are equal to 145.7×10^6 m^3 and 8.7×10^6 m^3, respectively. The constants of the surface-volume curve of reservoir [a_0 and a_1, see area storage Eq. (2)] are equal to 0.03 and 0.8, respectively (Ashofteh et al. 2015a). Maximum irrigation demand under the baseline and climatic-change conditions equal 39.57×10^6 m^3 and 47.24×10^6 m^3, respectively. Fig. 3 shows that the mean monthly inflow volume to the reservoir, the average monthly evaporation depth, and irrigation demand corresponding to the baseline and climatic-change conditions (Ashofteh et al. 2015a). It is seen in Fig. 3 that the inflow volume to reservoir and irrigation demand under climatic change will decrease by approximately 0.7% and increase by approximately 16%, respectively, relative to the baseline condition (Ashofteh et al. 2013a).

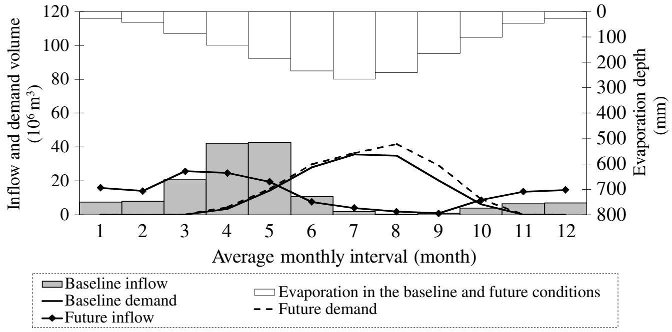

Fig. 3. Average monthly inflow volume to reservoir, average monthly evapotranspiration depth, and average monthly volume of water demand under baseline and climatic-change conditions

MO-GP Algorithm Parameters

The MO-GP algorithm was used to calculate MO operating rules under baseline and climatic-change conditions. The GPLAB GP toolbox (Silva 2007) in MATLAB version 11.0 (Overman 2011) was used for solution purposes. The parameters used in the MO-GP algorithm are listed in Table 2.

Evolutionary algorithms search for an optimal solution until no further improvement is achieved in the objective functions. It is noteworthy that the MO-GP algorithm was implemented in a computer outfitted with an Intel Core I7 processor, CPU 2.20 GHz, and RAM 6.00 GB. The execution time invested in solving the reservoir-optimization problem was approximately 10 h.

Results

Optimal operating rules for the Aidoghmoush Reservoir were calculated from a two-objective problem using the MO-GP algorithm. The two-objective problems were minimization of system vulnerability and maximization of the reliability of supplying irrigation demand. The positive constants [A', B', C', and D', Eqs. (9) and (10)] of the penalty values imposed on the objective functions are equal to 1, 0.5, 1, and 16, respectively. Fig. 4 shows the results of the MO-GP two-objective optimization algorithm in form of a Pareto curve for the baseline and climatic-change conditions. Each of the points on the Pareto curve represents a decision policy for extracting reservoir-operating rules or volumes of water to be released from reservoir storage under specified conditions.

It is seen in Fig. 4 that the value of the vulnerability index ranges between 16 and 41% and 11 and 35% under the baseline and climatic-change conditions, respectively, and that the value of the reliability index varies between 46 and 78% and 30 and 77% under the baseline and climatic-change conditions, respectively. Thus, the ranges of values of the vulnerability and reliability indices are larger under the climatic-change condition, and this might be caused by the future greater variability of input variables such as reservoir

Table 2. Parameters of the MO-GP Algorithm under Baseline and Climatic-Change Conditions

Parameter	Value
Generation number	300
Population size (tree number)	100
Functions used in the MO-GP	$\{+, -, \times, \div, \sin, \cos\}$
Mutation rate	0.1
Crossover rate	0.9

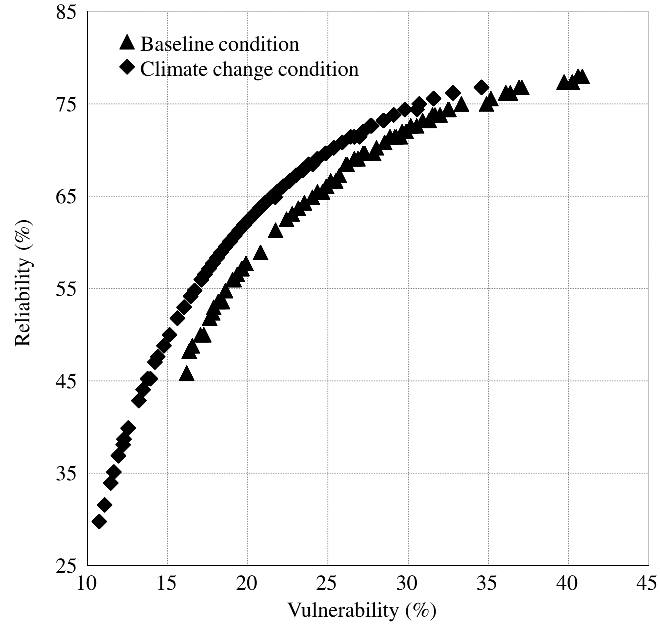

Fig. 4. Comparison of Pareto curves showing combination of values of the vulnerability and reliability objective functions associated with reservoir operation under baseline and climatic-change conditions

inflow. For a reliability of 50%, the system vulnerabilities under the baseline and climate change conditions are 17 and 15%, respectively. For a reliability of 75%, the system vulnerabilities under the baseline and climatic-change conditions are 33 and 31%, respectively. As the reliability increases, the vulnerability increases, also, and, that for the same level of reliability, the vulnerability is smaller under the climatic-change condition than that under the baseline condition. For a vulnerability of 20%, the system reliabilities under the baseline and climatic-change conditions are 58 and 61%, respectively, and for a vulnerability of 35%, the system reliabilities under the baseline and climatic-change conditions are 76 and 77%, respectively. Evidently, as the system vulnerability increases, so does its reliability under baseline and climatic-change conditions.

To illustrate the nature of the calculated reservoir-operation rules with the MO-GP algorithm, the ordered pairs $(Fu_1, Fu_2) =$ (17,50) (i.e., the vulnerability equals 17% and the reliability equals 50%) and $(Fu_1, Fu_2) =$ (15,50) under the baseline conditions are associated with the following operating rule:

$$\begin{aligned} Re_{bt} = {} & 1/\cos[\cos(Q_{bt}/D_{bt})]/\cos\{\cos\{\cos[(D_{bt}+S_{bt})/S_{bt}]\}\} \\ & /\cos\{\cos\{\cos[(S_{bt}+D_{bt}+Q_{bt})/S_{bt}]\}\} \\ & /\cos\{\cos[\cos(D_{bt}/S_{bt})/\sin(D_{bt})/D_{bt}/\sin[\cos(1)] \\ & /\cos(D_{bt})]\}/\{S_{bt}\cdot[S_{bt}+D_{bt}+\sin\{\cos[\cos(S_{bt})]\} \\ & -\cos(Q_{bt})]/D_{bt}/\{D_{bt}/\cos\{\cos[S_{bt}\cdot[S_{bt}+D_{bt}+\sin(D_{bt}) \\ & -\cos(Q_{bt})]/D_{bt}/(D_{bt}/Q_{bt}+D_{bt})]\}+D_{bt}\}+D_{bt}\}\cdot S_{bt} \end{aligned} \tag{14}$$

where Re_{bt} = rule developed in the baseline conditions by the MO-GP for the reliability of 50%.

The reservoir-operating rule for the pair $(Fu_1, Fu_2) = (15{,}50)$ under the climatic-change condition is

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$$
\begin{aligned}
Re_{ft} = {} & D_{ft} \cdot S_{ft} / \{S_{ft}^2 / \{S_{ft}^2 / (S_{ft} + 3D_{ft}) + D_{ft} + D_{ft} \\
& / S_{ft} \cdot \{2S_{ft} + S_{ft}^2 / \{S_{ft}^2 / \{S_{ft} + 3D_{ft} \cdot S_{ft} + D_{ft} \cdot S_{ft} \\
& / \{S_{ft}^2 / [\cos(D_{ft}) + Q_{ft} + 2D_{ft}] + D_{ft}\}\} + D_{ft} + 1 \\
& / S_{ft} \cdot [2S_{ft} + [D_{ft} + \cos(2S_{ft})] \cdot S_{ft} / (2Q_{ft} + D_{ft})] \\
& + \{S_{ft} + \sin[\sin(D_{ft}) \cdot S_{ft}] \\
& + \sin[\cos(3D_{ft})/D_{ft}]\} \cdot D_{ft}\}\}\} + D_{ft}\}
\end{aligned} \tag{15}
$$

where Re_{ft} = rule developed in the climatic-change conditions by the MO-GP for the reliability of 50%.

The reservoir-operating rule for the ordered pair $(Fu_1, Fu_2) = (33,75)$ under the baseline condition is

$$
\begin{aligned}
Re_{bt} = {} & 1/\cos\{\cos\{[\cos(D_{bt}) - D_{bt} \cdot Q_{bt} - Q_{bt}] \\
& / D_{bt}^2 / \cos\{(S_{bt} + D_{bt} + Q_{bt}) / D_{bt} \\
& / \{2D_{bt} + \sin[\cos(Q_{bt}/S_{bt})] \cdot Q_{bt}\}\}\}\} \\
& / \cos\{\cos\{\cos\{[S_{bt} + D_{bt} + \sin(D_{bt})]/S_{bt}\}\}\} \\
& / \cos\{\cos\{\cos[(S_{bt} + D_{bt} + 1)/S_{bt}]\}\} \\
& / \cos\{\cos\{\cos\{S_{bt} / \sin\{\cos[Q_{bt}/(2S_{bt} + D_{bt}) \cdot D_{bt}]\}\} \\
& / \sin(D_{bt})/D_{bt} / \sin\{\cos[S_{bt}/(D_{bt}^2 - Q_{bt})]\} \\
& / \cos(D_{bt})\}\}/(2S_{bt}/D_{bt} + D_{bt}) \cdot S_{bt}
\end{aligned} \tag{16}
$$

where Re_{bt} = rule developed in the baseline conditions by the MO-GP for the reliability of 75%.

The reservoir-operating rule for the pair $(Fu_1, Fu_2) = (31,75)$ under climatic change is

$$
\begin{aligned}
Re_{ft} = {} & D_{ft} \cdot S_{ft} / \{S_{ft}^2 / \{S_{ft}^2 / \{S_{ft} + 2D_{ft} + D_{ft} \cdot S_{ft} / \{S_{ft}^2 \\
& / \{\cos(S_{ft}) + 3D_{ft}/S_{ft} \cdot \{3S_{ft} + D_{ft} + [\cos(S_{ft}) \\
& + D_{ft}] \cdot \cos\{\cos\{(S_{ft} + 2D_{ft})/[S_{ft} + \sin(S_{ft}) \cdot Q_{ft}]\}\}\}\} \\
& + D_{ft}\}\} + D_{ft} + D_{ft}/S_{ft} \cdot \{2S_{ft} + S_{ft}^2/\{2S_{ft} + S_{ft}^2 \\
& / \{Q_{ft} + S_{ft}/Q_{ft} - D_{ft} + 2S_{ft} - \sin\{\{S_{ft} + D_{ft} + Q_{ft} \\
& / \cos[Q_{ft}/(D_{ft} + S_{ft} \cdot Q_{ft})] + \cos[(D_{ft} - S_{ft}) \\
& / \cos(Q_{ft}) \cdot D_{ft}]\}/S_{ft} - \cos[\sin(Q_{ft})]\}\}\}\}\} + D_{ft}\}
\end{aligned} \tag{17}
$$

where Re_{ft} = rule developed in the climatic-change conditions by the MO-GP for the reliability equal to 75%.

Fig. 5 shows (a) released volume, (b) storage volume, (c) spill volume, and (d) deficit volume corresponding to the optimal rules calculated with the MO-GP algorithm for the baseline period (1987–2000) under baseline conditions of reservoir inflow and irrigation demand (scenario 1), and for reliabilities equal to 50 and 75%. Fig. 6 presents the same variables as those shown in Fig. 5 corresponding to the second scenario, that is, applying the reservoir-operating rules calculated for the baseline period (those of scenario 1) to the reservoir receiving future reservoir inflow and subjected to future irrigation demand (the future or climatic-change period is 2026–2039). Fig. 7 presents the same variables shown in Figs. 5 and 6 associated with the third scenario, that is, applying the reservoir-operating rules calculated for the future period (2026–2039) using future reservoir inflow and demand.

It is seen in Figs. 5(a), 6(a), and 7(a) that the release associated with the third scenario is larger than that of the second scenario. This is due to a 16% increase of irrigation-demand volume (according to Fig. 3) in the third scenario (Ashofteh et al. 2013a). A comparison of the second and third scenarios shows that the release

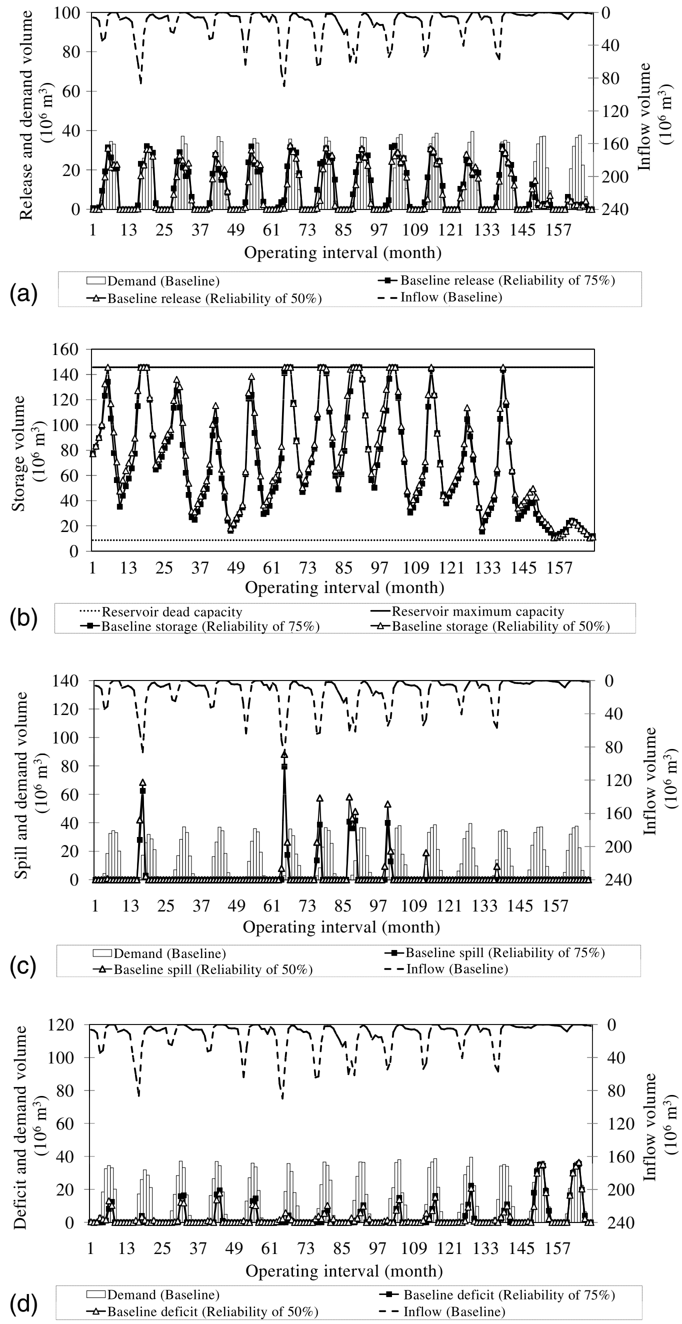

Fig. 5. Comparison of (a) released volume; (b) storage volume; (c) spill volume; (d) deficit volume, corresponding to the first scenario based on rule calculated with the MO-GP algorithm for Pareto points with reliabilities 50 and 75%, showing inflow to reservoir and volume of water demand in the operating interval

volume associated with the latter scenario is more consistent with irrigation demand. Figs. 5(b), 6(b), and 7(b) show that reservoir storage corresponding to the third scenario is smaller than those of the other two scenarios. This is caused by the larger releases in the third scenario. Figs. 5(c), 6(c), and 7(c) indicate that the spilled volume associated with the third scenario is the lowest, because the reservoir inflow volume is reduced by about 0.7% (according to Fig. 3) in the future period. Figs. 5(d), 6(d), and 7(d) show that reservoir performance improves in the third scenario.

Table 3 shows results concerning the performance of the reservoir in supplying the irrigation demand with reliabilities of 50 and

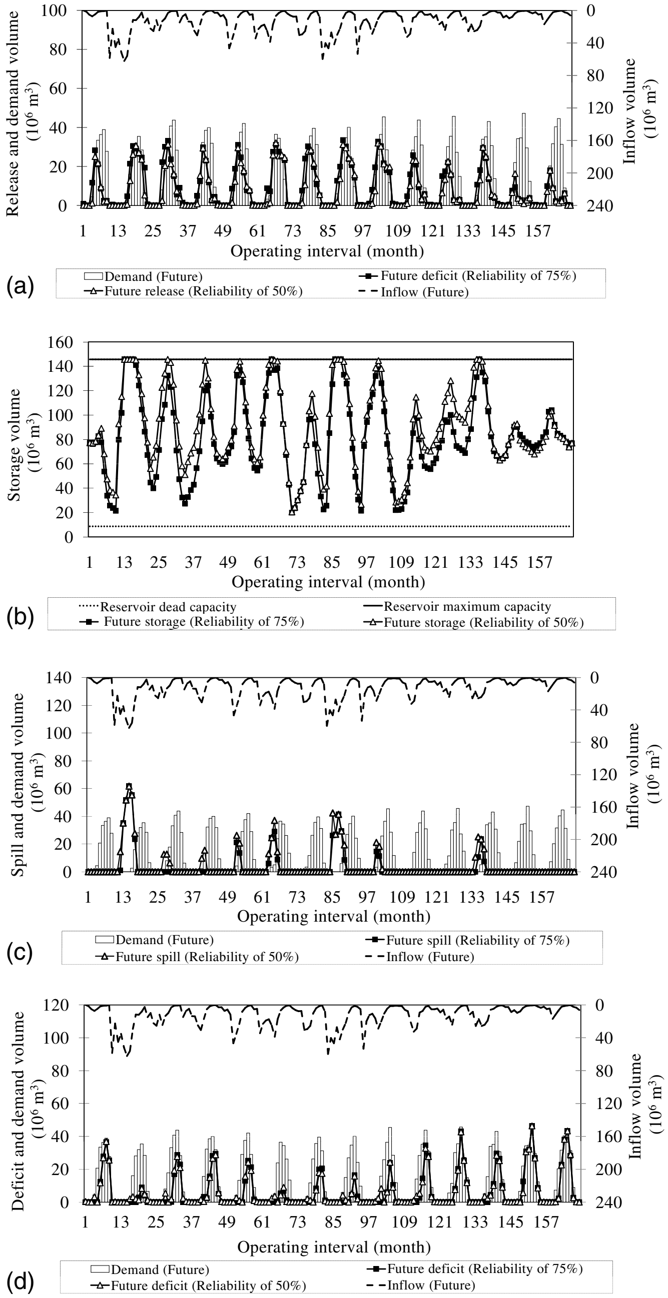

Fig. 6. Comparison of (a) released volume; (b) storage volume; (c) spill volume; (d) deficit volume, corresponding to the second scenario based on rule calculated with the MO-GP algorithm for Pareto points with reliabilities 50 and 75%, showing inflow to reservoir and volume of water demand in the operating interval

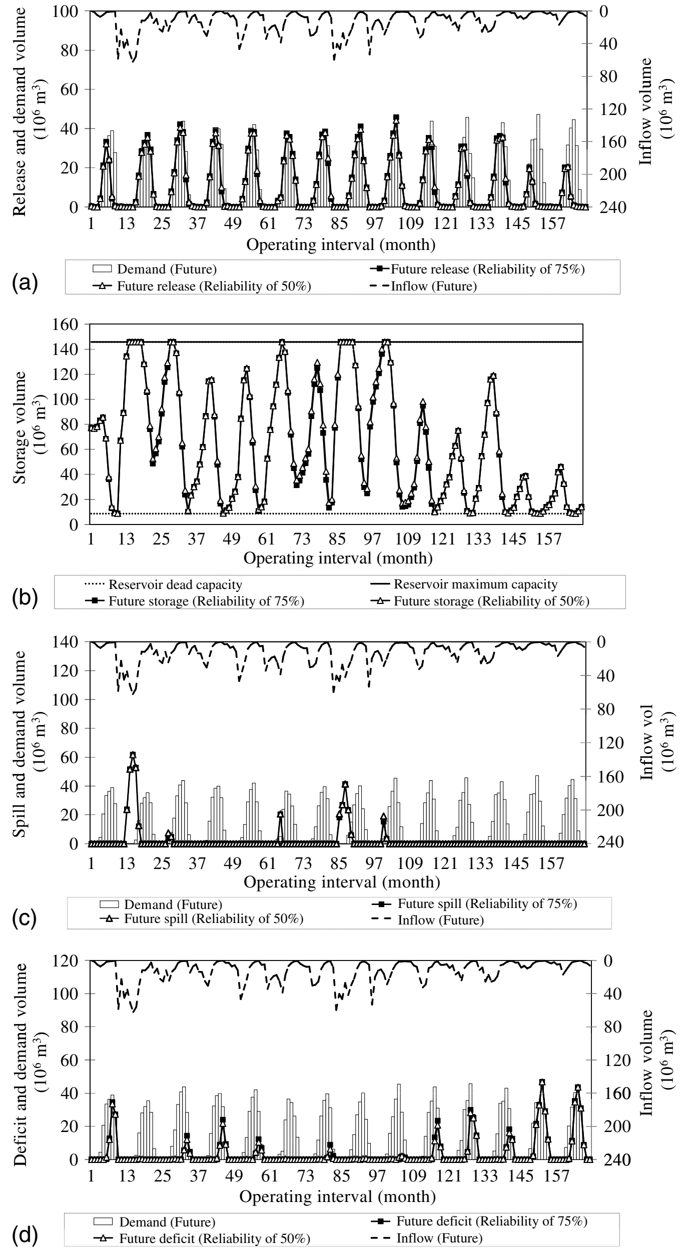

Fig. 7. Comparison of (a) released volume; (b) storage volume; (c) spill volume; (d) deficit volume, corresponding to the third scenario based on rule calculated with the MO-GP algorithm for Pareto points with reliabilities 50 and 75%, showing inflow to reservoir and volume of water demand in the related interval

75% under the three scenarios. The results in Table 3 demonstrate that the third scenario has a better performance relative to the other two scenarios. A comparison of the values of the objective functions corresponding to the first and second scenarios indicates that the application of baseline operating rules is not appropriate with future conditions of irrigation demand and reservoir inflow.

A comparison of the second and third scenarios in Table 3 shows that the values of objective function corresponding to reservoir operation under the third scenario are between 29 and 32% better than those associated with the second scenario. This proves that reservoir operation according to the third scenario is superior to the second scenario in meeting irrigation demand.

Table 3. Comparison of Objective Functions for Two Pareto Points (Reliabilities Equal to 50 and 75%) Associated with the Three Optimization Scenarios

	For Pareto point with reliability = 50%		For Pareto point with reliability = 75%	
Scenario	First objective function	Second objective function	First objective function	Second objective function
First	17	50	33	75
Second	21	38	36	64
Third	15	50	31	75

Concluding Remarks

The MO-GP algorithm was used for optimizing the operation of the Aidoghmoush Reservoir system (East Azerbaijan, northeast of Iran) under baseline and climatic-change conditions. Two objective functions were used in this study: minimization of the vulnerability index and maximization of the reliability index. This paper's methodology and results demonstrate that MO operation of reservoirs that accounts for changes in water demand and in river flow in a future period influenced by climatic change would lead to improved performance relative to that that would be expected if baseline reservoir-operating rules are extended into the future.

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