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ORIGINAL ARTICLE

Calculation of multi-objective optimal tradeoffs between environmental flows and hydropower generation

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Abstract

Reservoir operation commonly involves tradeoffs between the objective of meeting downstream environmental flows and hydropower generation that may call for high reservoir level to generate hydropower more efficiently. Fixed length gene genetic programming (FLGGP) is an optimization tool that searches the decision space of an optimization problem employing a variety of functions, mathematical operators, and variables. This paper develops the FLGGP as a multi-objective optimization method and compares its performance with that of the nondominated sorting genetic algorithm (NSGA)-II in calculating multi-objective reservoir operational rules. Results show the multi-objective FLGGP decreased (improved) 5.64 and 39.5% the environmental flow and hydropower generation objectives, respectively, relative to the NSGA-II's values.

Keywords Multi-objective optimization · Environmental flows · Hydropower generation · Fixed length gene genetic programming (FLGGP)

Introduction

The protection of riverine environments has led to the introduction of the concept of the environmental flow requirement that describes the amount of river flow required to maintain healthy riverine ecosystems. Various hydrological, hydraulic, habitat simulation, and holistic methods have been proposed to calculate environmental flow requirements.

Acreman and Dunbar (2004) reviewed the definition environmental river flow requirements. Smakhtin et al. (2006) applied the hydrologic method to assess environmental flows of East Rapti River in Nepal. Suen (2011) applied a long-term series of river flow for 58 stations and 23 rivers in Taiwan to estimate flow requirements. Shokoohi and Hong (2011) determined minimum ecological water requirements in the Perennial River using morphological parameters. Meijer et al. (2012) applied the generic water resources planning package 'RIBASIM' to calculate environmental flow release in the Mahabad basin in Iran. Bhattacharjee and Jha (2014) employed indicators of hydrological alternations (IHA) to estimate environmental flow in the Mahanadi River Basin, India. Kim and Singh (2014) applied the IHA by Richter et al. (1998) with the IHA software in the Geum River in South Korea. Munoz-Hernandez et al. (2011) developed an integrated hydrologic-economic-institutional water model for the Rio Yaqui Basin, northwestern Mexico. They focused on the creation of simulation models that estimate the agricultural net benefits under different environmental flow scenarios and surface water allocation strategies.

In all the aforementioned investigations, the flow requirement was estimated considering river conditions. However, there are other stakeholders with competing objectives such as water consumers. Optimization algorithms are appropriate tools to optimize multiple objectives simultaneously. There are several methods for multi-objective optimization in the field of water resources systems. Reddy and Kumar (2006) applied the multi-objective genetic algorithm (MOGA) to determine flexible operational polices for a multipurpose

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reservoir system. Afshar et al. (2013) implemented multi-objective particle swarm optimization (MOPSO) to multi-objective calibration of reservoir water quality modeling considering a combined measure of thermal and reservoir water level as the first objective, and the forecasting physical, chemical, and biological variables as the second objective. Kougias and Theodossiou (2013) proposed the harmony search algorithm (HSA) to find optimal solutions in a pump scheduling problem. Yang et al. (2013) implemented a fuzzy multi-objective model for petroleum-contaminated aquifer remediation with the objectives of minimizing the pumping rate, and minimizing the average post-remedial contaminant concentration.

This paper determines an optimal reservoir system operational rule considering as objectives the provision of environmental flow and the generation of hydropower energy. The MFLGGP was developed for this purpose and its results were compared with those of the NSGA-II, a competing and leading multi-objective optimization method.

Reservoir system simulation

Reservoirs are artificial lakes that store water and release it at suitable times to meet a variety of functions such as supplying downstream water demands, generating hydropower energy, and flood control. Operational decision rules are mathematical and/or logical equations that determine the value of reservoir release in each period of operation. A general mathematical rule curve is as follows:

$$R_t = F(\mathbf{X}_t) \tag{1}$$

in which R_t is the reservoir release (the dependent variable), F is the mathematical function for calculating reservoir releases, and $\mathbf{X}_t$ is a vector of input variables such as reservoir storage, inflow to the reservoir, and the amount of downstream water demand which are the independent variables at time t.

A linear decision rule is a common pattern of the rule curve that is calculated as follows (e.g., Mousavi et al. 2007; Bozorg-Haddad et al. 2008):

$$R_t = A \times I_t + B \times S_t + C, \tag{2}$$

where S_t is the reservoir storage at time t, I_t is the inflow to the reservoir in period t,A, B and C are coefficients hat are determined as the decision variables by means of optimization. More effective operational rules than that of Eq. (2) have been proposed. This paper presents a multi-objective approach to optimal reservoir operational rule calculation. The reservoir operational rule herein developed does not assume any a priori mathematical form of the rule, such as that given by a linear rule in Eq. (2). Rather, this paper develops multi-objective fixed length gene genetic programming (MFLGGP) to calculate a reservoir operational rule that finds the optimal tradeoff that arises between meeting downstream environmental flow requirements and generating hydropower energy.

The continuity equation of a reservoir is written as follows:

$$S_{t+1} = S_t + I_t - R_t - \mathrm{SP}_t - \mathrm{Loss}_t \tag{3}$$

in which S_t, S_{t+1} are the reservoir storage, respectively, at the beginning and end of each operational period t, SP_t is the volume of spilled water from reservoir during period t, and Loss_t is the volume of water loss from reservoir (evaporation).

Reservoir operation is constrained by the following equations:

$$\mathrm{Loss}_t = f_1(\mathrm{Ev}_t, \overline{A_t}) \tag{4}$$

$$\overline{A_t} = (A_t + A_{t+1})/2 \tag{5}$$

$$A_t = f_2(S_t) \tag{6}$$

$$0 \leqslant R_t \leqslant D_t \tag{7}$$

$$S_{\mathrm{Min}} \leqslant S_t \leqslant S_{\mathrm{Max}}, \tag{8}$$

where f_1 is the function for calculating the volume of evaporation during a operation period, Ev_t is the evaporation depth, $\overline{A_t}$ is the average reservoir (water) surface during period t, A_t, A_{t+1} is the reservoir surface, respectively, of the at the start and end of each operational period t, f_2 is the function that calculates reservoir surface from reservoir storage, and S_{Min}, S_{Max} is the minimum and maximum reservoir storage, respectively.

Hydropower generation

The objective of generating hydropower energy is to generate hydropower as close to the installed capacity as possible during the operational periods. This objective is written as the following minimization:

$$\text{Min. } Z_1 = \frac{\sum_{t=1}^{T} (\mathrm{PPC} - P_t)}{\mathrm{N}_{t=1}^{T}(P_t < \mathrm{PPC})} \tag{9}$$

in which Z_1 is the objective function for hydropower generation,P_t is the generated power during period t, and PPC is the installed capacity of the power plant.

Additional equations for hydropower energy generation are as follows:

$$P_t = f_3(\gamma, e, R_t, \mathrm{PF}, \overline{H_t}, \mathrm{TW}_t) \tag{10}$$

$$\overline{H_t} = (H_t + H_{t+1})/2 \tag{11}$$

$$H_t = f_4[(S_t)^3] \tag{12}$$

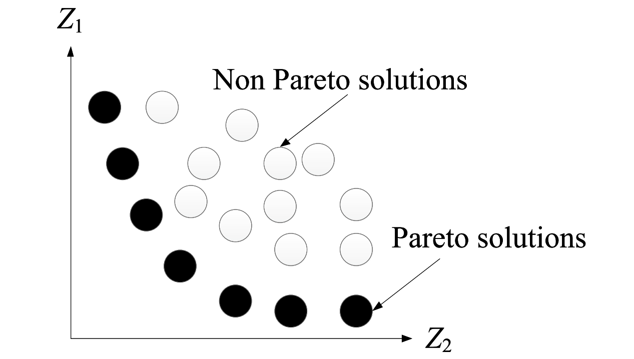


Fig. 1 Dominated and nondominated solutions for a bi-objective minimization problem

$$\mathrm{TW}_t = f_5[(R_t)^3] \tag{13}$$

in which f_3 is the function to calculate the hydropower generated, γ is the specific weight of water; e is the efficiency of the power plant, PF is the plant factor; $\overline{H_t}$ is the average head of the reservoir during period t; H_t, H_{t+1} is the water elevation in the reservoir at the start and end of period t, respectively, TW_t is the tailwater elevation during period t, f_4 is the function for calculating reservoir water level from storage, and f_5 is the function for calculating the tailwater elevation from the release R_t.

Environmental flow requirement

The environmental flow requirement is the flow rate needed in a river reach downstream from a reservoir to preserve a healthy riverine ecosystem. The objective in this case is to minimize the normalized absolute deviation between reservoir release and the environmental flow:

$$\text{Min. } Z_2 = \sum^{T} \frac{|D_t - R_t|}{D_t} \tag{14}$$

in which Z_2 is the objective function of meeting environmental flow requirements; T is the number of operating periods; and D_t is the environmental flow requirement during period t.

Multi-objective optimization tools

Multi-objective optimization methods search for the best sets of decisions that represent the tradeoffs between multiple objectives. These methods are classified in two categories: (1) traditional techniques that transform multi-objective problems to single-objective ones, and (2) evolutionary algorithms that calculate a set of nondominated solutions as a Pareto front for multi-objective problems. There is no implied preference for any of the nondominated solutions of a Pareto front. Rather, the improvement of one objective implies the worsening of another one. Moreover, the set of solutions on a Pareto front dominates any other set of solutions whose objective values are inferior to those on the Pareto front. Figure 1 presents the concept of dominated and nondominated solutions in a bi-objective problem with minimization objectives. The filled circles in Fig. 1 denote solutions on a Pareto front, which dominate the solutions denoted by unfilled circles. This paper compares the MFLGGP and NSGA-II multi-objective evolutionary algorithms in their capacity to calculate reservoir operational rule curves.

Multi-objective fixed length gene genetic programming (MFLGGP)

MFLGGP is an evolutionary computational algorithm in which each chromosome (the jargon for a possible solution to an optimization problem) represents a polynomial mathematical expression. Figure 2 shows a set of chromosomes form a decision matrix with $N \times D$ dimensions, in which N and D are identified as the number of chromosomes

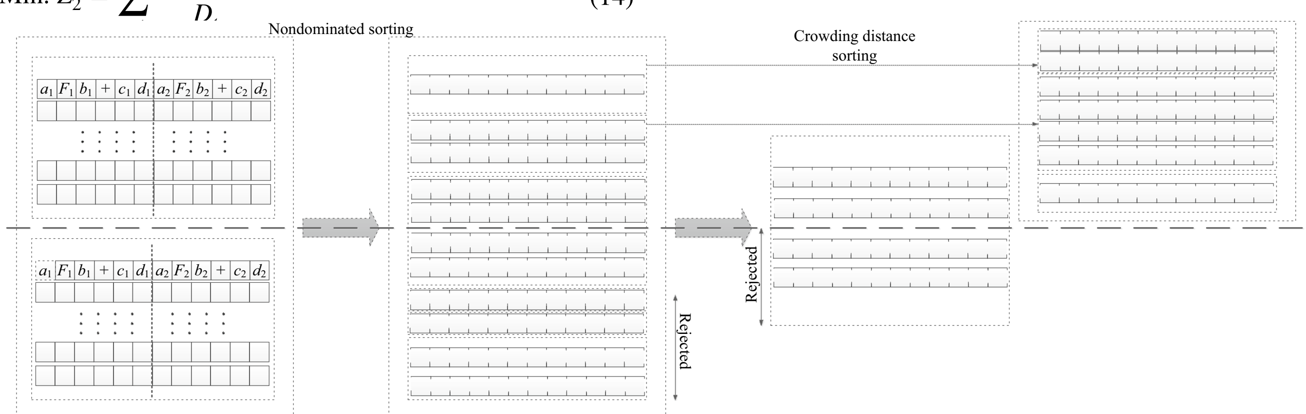


Fig. 2 Structure of the MFLGGP

(solutions) and decision variables (genes), respectively. Each chromosome can be represented with a function of the form $Y = [a(F((X)^b)) + c]^d$, where X and Y represent input and decision variables, respectively. Chromosomes a, b, c, and d are numerical variables identical to those of a gene in NSGA-II, and F is a mathematical function such as sin, cos, or log which is selected from a function set. A population of solutions (chromosomes) is classified with a mathematical operator. As an example, the mathematical operator for the fourth gene is chosen from $\{+, -, \times, \div\}$. This population of solutions is then classified using Eq. (15):

$$d_{I_j} = \sum_{m=1}^{M} \frac{Z_m^{I_{j+1}^m} - Z_m^{I_{j-1}^m}}{Z_m^{\mathrm{Max}} - Z_m^{\mathrm{Min}}}, \tag{15}$$

where d_{I_j} is the crowded distance of the $j$thsolution, M is the number of objectives, $Z_m^{I_{j-1}^m}$ and $Z_m^{I_{j+1}^m}$ is the values of the mth objective for the $(j-1)$th and $(j+1)$th solutions, Z_m^{Min} and Z_m^{Max} are minimum and maximum value of the mth objective function among the solutions of the current population of solutions.

Pareto fronts are ranked using two criteria: (1) a nondominated rank, and (2) a crowding distance in the population of solutions (Fallah-Mehdipour et al. 2012). The next step is to improve the quality of the current best Pareto front. Deb and Agrawal (1995) applied the simulated binary crossover (SBX) operator to combine two chromosomes (or parent solutions) and create two new chromosomes (or children solutions). This simulated binary recombination (crossover) operator is similar to one-point cut crossover. In this operator, the crossover probability distribution is calculated as follows:

$$P(\beta_i) = 0.5(\eta_c + 1)\beta_i^{\eta_c} \quad \beta_i \leqslant 1 \tag{16a}$$

$$P(\beta_i) = 0.5(\eta_c + 1)\frac{1}{\beta_i^{\eta_c+2}} \quad \beta_i > 1 \tag{16b}$$

$$\beta_i = (2\mu_i)^{\frac{1}{\eta_c+1}} \quad \mu_i \leqslant 0.5 \tag{17a}$$

$$\beta_i = \left(\frac{1}{2(1-\mu_i)}\right)^{\frac{1}{\eta_c+1}} \quad \mu_i > 0.5, \tag{17b}$$

where $P(\beta_i)$ is the crossover probability, β_i is the difference between parents and children objective functions, η_c is a constant value, whereby a large value of η_c gives a higher probability for creating near-parent solutions than would otherwise be, and μ_i is a random value in [0, 1]. Equations (18)–(20) determine the children's values with Equations (16a, 16b) and (17a, 17b):

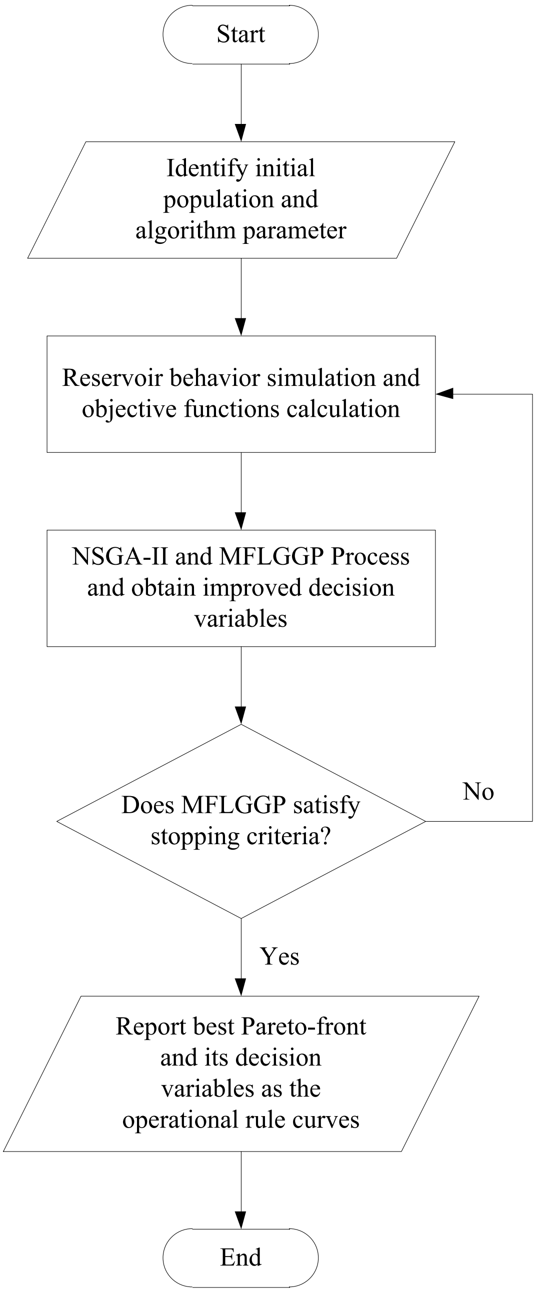


Fig. 3 Flowchart of simulation–optimization process

$$\beta_i = \left| \frac{x_1^{\mathrm{child}} - x_2^{\mathrm{child}}}{x_1^{\mathrm{parent}} - x_2^{\mathrm{parent}}} \right| \tag{18}$$

$$x_1^{\mathrm{child}} = 0.5\left[(1+\beta_i)x_1^{\mathrm{parent}} + (1-\beta_i)x_2^{\mathrm{parent}}\right] \tag{19}$$

$$x_2^{\mathrm{child}} = 0.5[(1-\beta_i)x_1^{\mathrm{parent}} + (1+\beta_i)x_2^{\mathrm{parent}}], \tag{20}$$

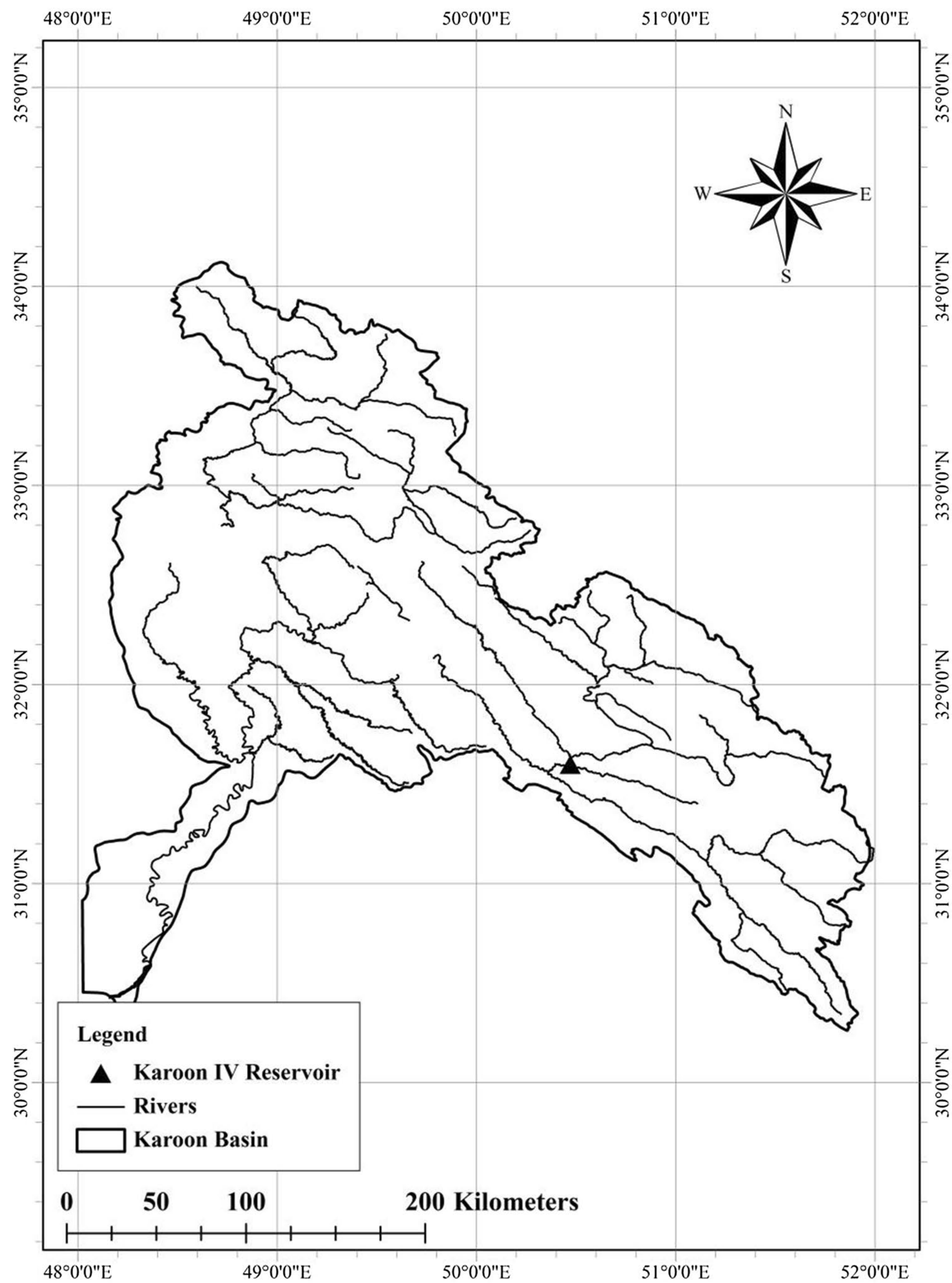


Fig. 4 Location of the Karoon IV reservoir within the Karoon Basin

where x_1^{child} and x_1^{parent} are value of the first child and parent chromosomes, respectively, and x_2^{child} andx_2^{parent} are value of the second child and parent chromosomes, respectively.

Mutation is the other genetic operator that has been proposed in a polynomial form by Deb and Goyal (1996) as follows:

$$\delta_i = \begin{cases} (2r_i)^{1/(\eta_m+1)-1} & r_i < 0.5 \\ 1 - [2(1-r_i)^{1/(\eta_m+1)}] & r_i \geqslant 0.5 \end{cases} \tag{21}$$

$$x^{\text{child}} = x^{\text{parent}} + \delta \tag{22}$$

in which δ is the mutation value, r_i is the random value in [0, 1] and η_m is the distribution constant of mutation. The combination of parents' and children's chromosomes engenders the new population for next generation. This process of generating new populations of solutions and improving them continues until reaching the maximum number of generation. Thus, the MFLGGP structure is similar to the NSGA-II's with a new advantage being that it is capable of using functions and operators for forming mathematical expressions. This added capacity renders MFLGGP more flexible than the NSGA-II

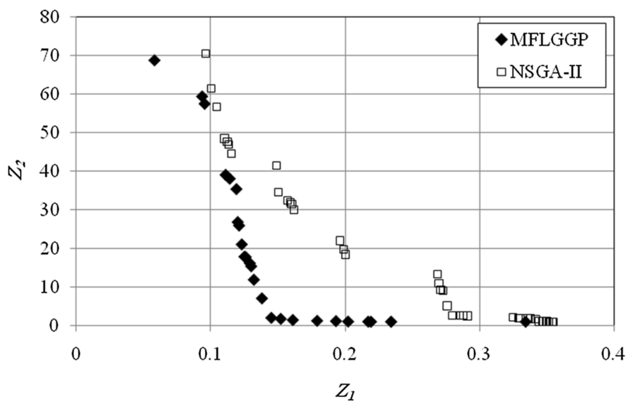


Fig. 5 Optimal Pareto fronts calculated with MFLGGP and NSGA-II

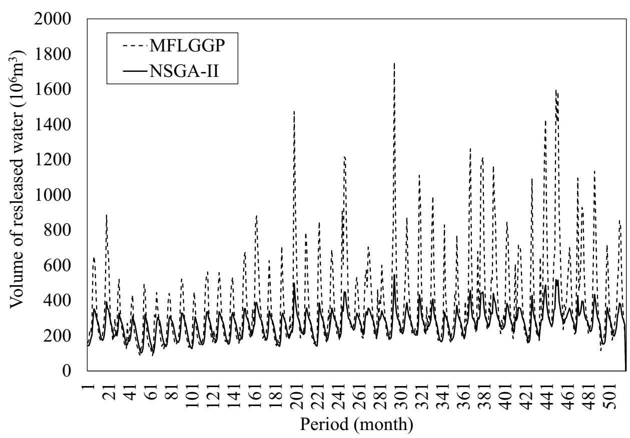
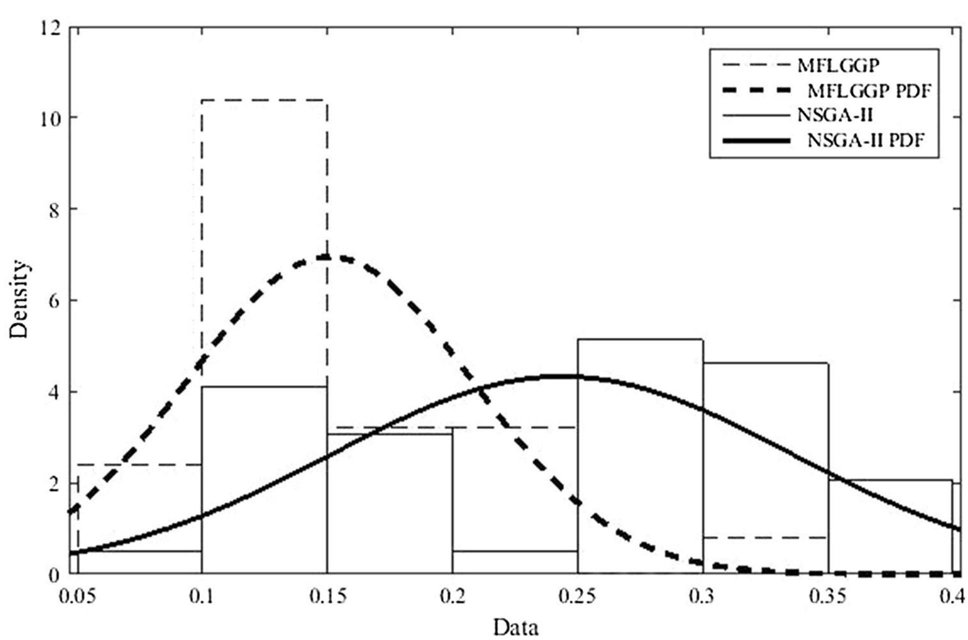


Fig. 6 Volume of released water from Karoon IV reservoir

Fig. 7 Z_1 PDF corresponding to the MFLGGP and NSGA-II



in dealing with chromosomes as numerical variables that can be subjected to a wide variety of mathematical representations. Figure 3 illustrates simulation–optimization process of this paper.

Case study

The Karoon River flow through the basin with the same name, issuing from the Zagros Mountains. Other rivers such as Kiar and Shalamzar are tributaries to the Karoon river, which flows through southwestern Iran. Karoon IV as an arch dam reservoir on the Karoon River, before it joins the Khersan River at location with geographical coordinates of 31°35′ northern latitude and 50°43′ eastern longitude, southwest of Shahr-e-Kord in the province of Chaharmahal and Bakhtiari, Iran. Figure 4 depicts the location of the Karoon IV reservoir in Karoon Basin. This reservoir with an annual average inflow of $4982 \times 10^6\,\mathrm{m}^3$ is one of the largest reservoirs in the Karoon river basin. The reservoir is operated for hydropower energy generation. Minimum and maximum allowable storage volumes are 1440×10^6 and $2190 \times 10^6\ \mathrm{m}^3$, respectively. The environmental flow requirement of the Karoon River downstream of the reservoir is calculated by the Tennant method (1976).

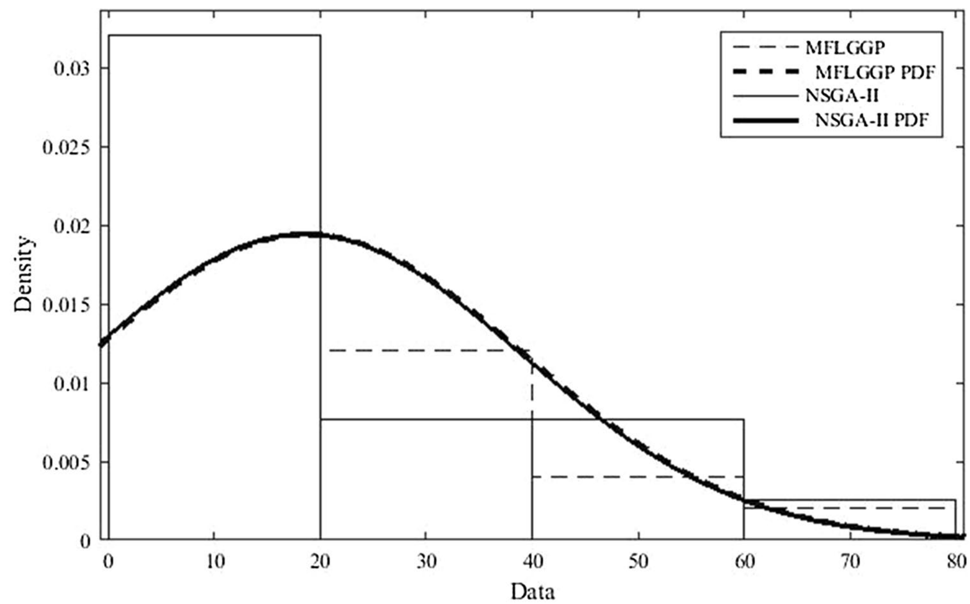


Fig. 8 Z_2 PDF corresponding to the MFLGGP and NSGA-II

Results and discussion

Hydropower energy generation and provision of environmental flows are important functions of reservoir operation. This paper's case study considers two conflicting objectives: (1) hydropower energy generation that seeks to keep a high reservoir level to achieve efficient hydropower production, and (2) meeting the environmental river requirement that tends to draw down reservoir storage. Equations (9) and (14) represent the hydropower production and environmental flow objective functions, and the optimal Pareto fronts for the reservoir operational rules were calculated with NSGA-II and MFLGGP. The number of functional evaluations herein implemented equals 20,000 with 20 chromosomes and 1000 generations.

Figure 5 depicts the calculated Pareto fronts with NSGA-II and MFLGGP. It is evident from Fig. 5 the Pareto front by MFLGGP dominates the NSGA-II-calculated Pareto front, with the MFLGGP achieved Pareto front composed of smaller values of the objective functions than those of the NSGA-II calculated Pareto front. In other words, there are two different Z_2 calculated by the NSGA-II and MFLGGP for the same value of Z_1. For example, if the value of Z_1 is 0.2, the value of Z_2 is, respectively, equal to 0.92 and 18.4 by the MFLGGP and NSGA-II. In this case, although the value of reliability for generating hydropower energy is 77 using both optimization tools, the values of reliability for supplying environmental demand equal 98 and 83 by MFLGGP and NSGA-II, respectively. Figure 6 shows released water from Karoon IV reservoir according to the calculated rule curves. It is seen in Fig. 6 released water calculated with the LDR during the operational horizon by NSGA-II is limited to a narrow range, whereas released water calculated with the MFLGGP falls within a much wider range. The wider range achieved by MFLGGP demonstrates its superior performance compared to the LDR. Moreover, Figs. 7 and 8 display histogram and probability density function (PDF) for Z_1 and Z_2, respectively. It is seen in Figs. 6 and 7, the probability of determining optimal solutions is higher for MFLGGP than for the NSGA-II.

Reservoir operational rules help the operator in making appropriate decisions to determine how much (amount) and when (time) to release water from the reservoir. According to the obtained Pareto front shown in Fig. 5, each point corresponds to a rule curve with different stakeholder's utilities. For instance, the middle MFLGGP Pareto front point, (0.12, 26.8)corresponds to supplying half of the hydropower generation and environmental flow requirement utilities. On the other hand, the end points of the Pareto front meet maximum levels of Z_1 and Z_2 corresponding to hydropower generation and environmental flow requirement utilities. The LDR rule curve is linear and its coefficients were extracted by NSGA-II. Linear Eqs. (23) and (24) calculate water releases from the reservoir considering Q_t and S_t obtained with the NSGA-II.

Minimization of the deficit of hydropower generation:

$$R_t = 0.05(Q_t) + 0.21(S_t - S_{\text{min}}) + 2. \tag{23}$$

Minimization of the environmental flow deficit:

$$R_t = 0.87(Q_t) + 0.75(S_t - S_{\text{min}}) + 1.89. \tag{24}$$

This linear assumed pattern limits release to known specified formulation, whereas the MFLGGP formulation has more degrees of freedom. The superiority of the MFLGGP is due to its greater flexibility relative to the NSGA-II.

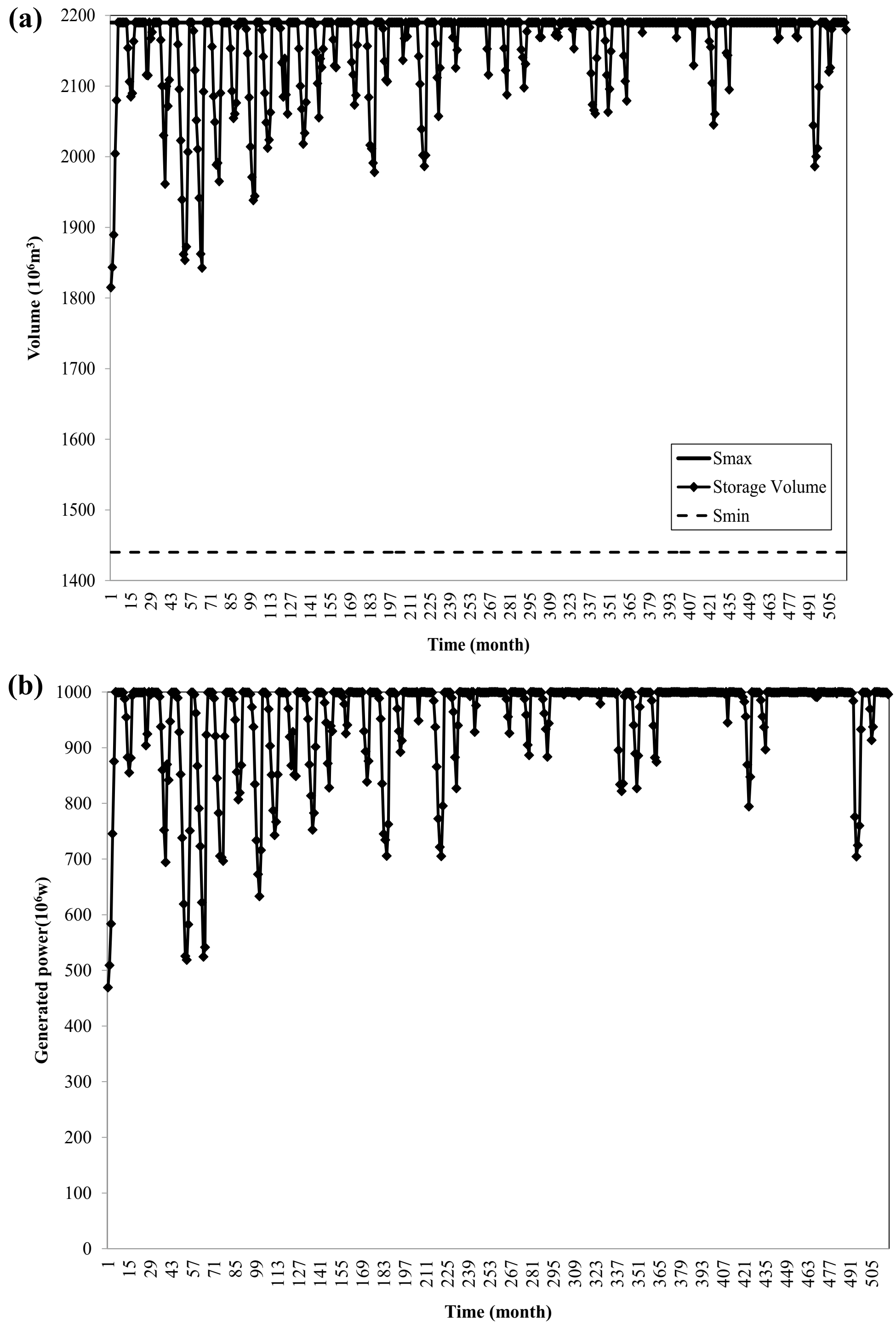


Fig. 9 Trend of **a** reservoir storage, and **b** generated power, corresponding to the minimum values of Z_1

Specifically, the NSGA-II relies on decision variables that are limited to numerical variables dictated by the linear decision rule for reservoir operation. The MFLGGP, on the other hand, relies on numerical variables, mathematical functions, and arithmetic operators in its structural representation of operational rules, rendering the latter highly flexible. Equations (25) and (26) express the calculation of reservoir releases for minimizing the deficits of hydropower energy generation and environmental flow, respectively, obtained with the MFLGGP:

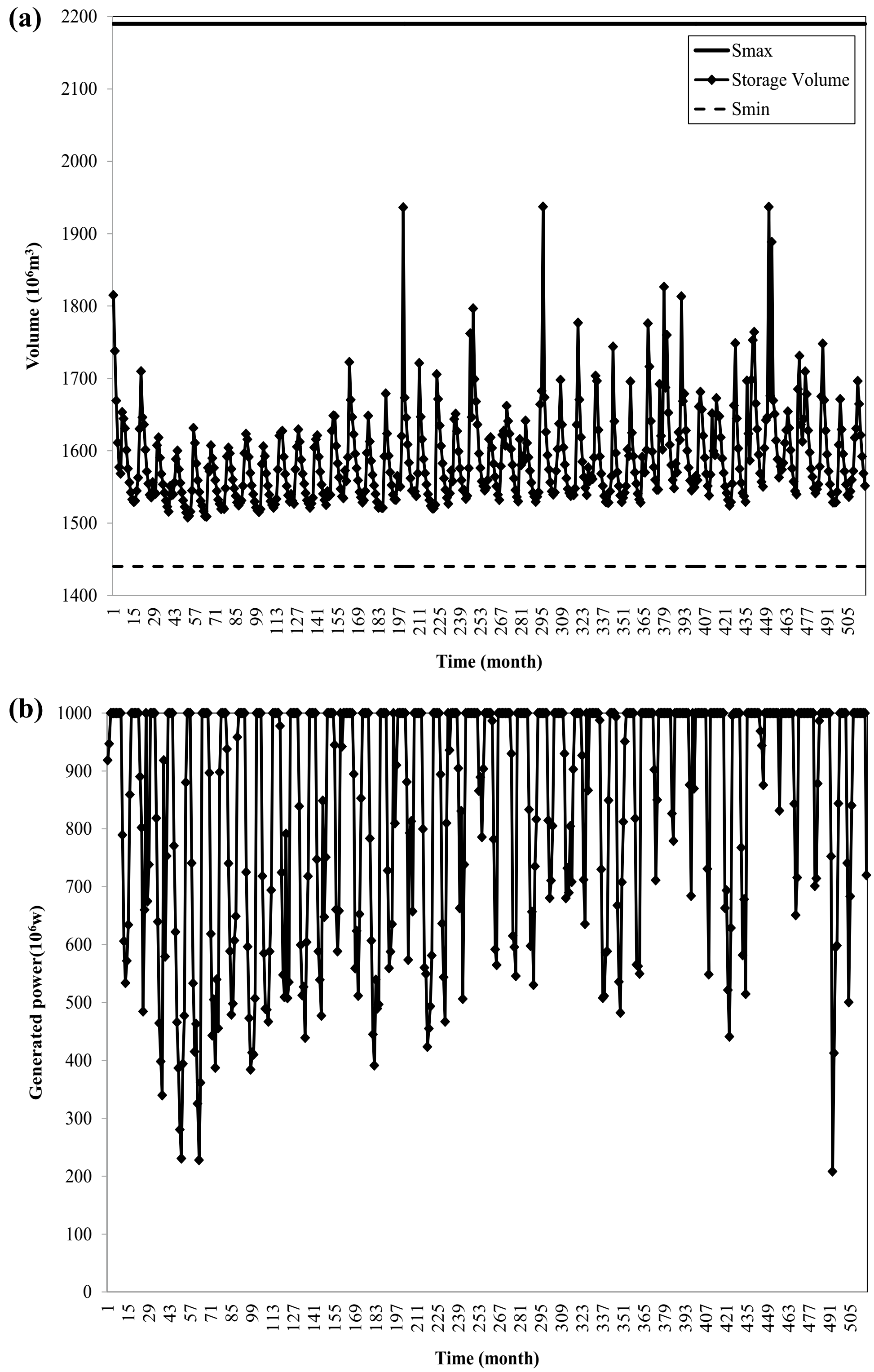
Minimization of the deficit of hydropower generation:

$$R_t = [0.06(Q_t)^{0.17} + 0.76(S_t - S_{\min})^{0.95} - 0.853]^{0.87}. \quad (25)$$

Minimization of the environmental flow deficit:

$$R_t = [0.53(Q_t)^{0.95}(S_t - S_{\min})^{0.34} + \sin(0.623)]^{0.89}. \quad (26)$$

Fig. 10 Trend of **a** storage volume and **b** generated power, corresponding to the minimum values of Z_2



Equations (23) and (24) involve power laws and arithmetic operators that represent nonlinear reservoir operational rules. Figures 9 and 10 depict the evolution of reservoir storage and generated power corresponding to the minimum values of the objective functions Z_1 and Z_2, respectively.

Concluding remarks

Optimal reservoir operation is intrinsically multi-objective, including objectives such as provision of environmental flow and hydropower energy generation. These objectives are commonly conflicting concerning the management of reservoir storage and releases. Recently, the application of FLGGP for developing optimal reservoir operational rules has improved performance of the calculated reservoir operational rules compared to those obtained with other methods. This paper applied FLGGP to develop the best relation between inflow, volume storage, and release as the operational rule curve for two operational purposes: provision of environmental flow and generating hydropower energy. The best tradeoff between mentioned purposes was determined with a linear decision rule solved with NSGA-II and with the MFLGGP. Results showed the MFLGGP finds nondominated solutions with minimum distance from ideal points/solutions. The quality of the Pareto front is important when solving multi-objective optimization problems. The number of Pareto front points and their spread in solution spread measure the quality of a Pareto front. Calculated optimal MFLGGP Pareto fronts exhibited excellent performance with 25 points, appropriate spread from 0.06 to 0.33 associated with the first objective, and 0.87–68.8 associated with the second objective. These calculated traits show the proposed MFLGGP produces flexible and efficient reservoir operation for the evaluated objectives. Application of MFLGGP in the optimal operation of a reservoir with other operation purposes, such as flood control, is recommended for future studies.

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