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Development of a Comparative Multiple Criteria Framework for Ranking Pareto Optimal Solutions of a Multiobjective Reservoir Operation Problem

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Abstract: Real-world, multiobjective, reservoir optimization problems (MOOPs) usually have conflicting objective functions. Multiobjective evolutionary algorithms (MOEAs) have been applied to solve multiobjective optimization problems. Given that MOOP solutions cannot minimize or maximize all objectives simultaneously, it is difficult to determine Pareto optimal solutions (POS). This paper presents a comparative multimethodological framework that implements five multicriteria decision-making methods (MCDMs) to determine POS for a single-reservoir system with three objective functions. The Borda technique was successfully employed to rank the MCDMs' solutions. The reservoir system's release, storage, and generated hydropower were optimized based on the best-ranked MCDMs' solutions. This paper's methodology introduces practical computational framework for making robust decisions in complex reservoir operation problems and demonstrates its applicability. **DOI: 10.1061/(ASCE)IR.1943-4774.0001028.** *© 2016 American Society of Civil Engineers.*

Author keywords: Multiobjective optimization problem; Multicriteria decision making-Pareto frontier; Reservoir operation; Nondominated sorted genetic algorithm-II (NSGA-II).

Introduction

Many real-world engineering problems have to satisfy multiple and sometimes conflicting objective functions while meeting constraints (Hiwa et al. 2015). The optimal operation of reservoir systems commonly faces inherent trades-off among various conflicting factors as most multiobjective optimization problems (MOOPs) do. Water-resources MOOPs are plagued by such mathematical issues as nonlinearity, stochasticity, discreteness, nonconvexity, high dimensionality, rapid combinatorial growth rates, and uncertainty (Reed et al. 2013). Classical optimization methods such as linear programming (LP), nonlinear programming (NLP), dynamic programming (DP), and stochastic dynamic programming (SDP) cannot obtain optimal solutions in complex discrete or nonlinear problems. Furthermore, the curse of dimensionality in solving large-scale problems is another limitation of classical optimization methods (Deb 2001; Fallah-Mehdipour et al. 2012b). To overcome the aforementioned limitations, evolutionary algorithms (EAs) have become a preferred alternative for solving complex water resources optimization problems. A few examples are site selection (Karimi-Hosseini et al. 2011; Bozorg-Haddad et al. 2015a), groundwater management (Bozorg-Haddad and Mariæo 2011; Ebrahim et al. 2015), cultivation rules and irrigation allocation (Noory et al. 2012; Ashofteh et al. 2015; Lalehzari et al. 2015), hydrology (Orouji et al. 2013; Taormina and Chau 2015), water distribution networks (Beygi et al. 2014; Rahmani et al. 2015), hydraulics (Werisch et al. 2014; Saldarriaga et al. 2015), pollution control (Shokri et al. 2014; Amirkani et al. 2015), evapotranspiration estimation (Shamshirband et al. 2015), and reservoir system operation (Fallah-Mehdipour et al. 2011, 2012a, 2013; Kang and Park 2014; Cheng et al. 2015; Bozorg-Haddad et al. 2015b).

Multiobjective evolutionary algorithms (MOEAs) have been successfully used by various scholars in the field of reservoir operation (Rampazzo et al. 2015). In this regard, Luo et al. (2015) developed a hybrid MOEA to optimally solve a reservoir flood control operation in China. Schardong and Simonovic (2015) applied a hybrid MOEA to formulate a reservoir operation MOOP involving two conflicting objectives in southwestern Brazil.

MOOPs often involve conflicting criteria. Thus, there is no single optimal solution that can simultaneously satisfy all the criteria. For this reason MOOPs search for nondominated optimal solutions that are considered as near-optimal solutions for any combination of proposed objective functions (Ahmadi et al. 2014). Deb et al. (2002) developed the nondominated sorting genetic algorithm-II (NSGA-II) to extract MOOPs solutions that are called Pareto frontiers or Pareto optimal solutions (POSs). The NSGA-II has been applied in multiple fields. For instance, NSGA-II outperformed multiobjective particle-swarming optimization (MOPSO) to solve a construction management problem (Fallah-Mehdipour et al. 2012b). Hassaballah et al. (2012) applied the NSGA-II for determining optimal rules of the Mandaya Reservoir in Ethiopia. Mohammad-Rezapour-Tabari and Soltani (2013) applied the NSGA-II as a multiobjective optimization model for conjunctive

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management. Hajiabadi and Zarghami (2014) implemented the NSGA-II for the multiobjective optimization of the Sefidrud reservoir in Northern Iran. Mala-Jetmarova et al. (2015) successfully applied the NSGA-II to assess the impacts of water quality of source reservoirs on the optimal operation of a regional multiquality water distribution system. The application of the NSGA-II for reservoir operation by Tsai et al. (2015) illustrated that human and ecosystem needs were optimally met with the application of MOEAs.

The performance of reservoir systems has been evaluated with various indices. Jain and Bhunya (2008) pointed out that the use of one performance criterion does not highlight the strengths and weaknesses of reservoir operation policies. This study applied three simultaneous performance criteria involving reliability (Z_1), resiliency (Z_2), and vulnerability (Z_3) as the objective functions of the reservoir operation problem. Based on Hashimoto et al. (1982), Z_1, Z_2, and Z_3 answer the following questions:

- How likely is it that a [reservoir] system will fail?
- How rapidly can it be rehabilitated after a failure? and
- How dire are the impacts of a failure?

Based on Srdjevic et al. (2004), two crucial roles of the performance criteria in long-term reservoir operation include measuring the effects of alternatives and serving as the evaluation criteria through a multicriteria decision-making (MCDM) framework.

Due to the fact that MOOP solutions (POSs) cannot minimize or maximize all objectives simultaneously, it is necessary to construct tradeoff curves among objectives (Farmani et al. 2009; Hiwa et al. 2015). Thus, generation of appropriate Pareto solutions is a nontrivial issue that has caused much debate among scholars. MCDMs have been employed by various authors to choose an alternative that most appropriately satisfies the objectives of a problem. To mention a few of them, the following studies can be taken into account: selecting subsea pipeline routes (Balogun et al. 2015), flood risk prioritization (Malekian and Azarnivand 2015), assessment of irrigation water quality (Bozdağ 2015), lake restoration (Banihabib et al. 2015), pollution control (Ahmadi et al. 2015), flood management (Ahmadisharaf et al. 2015), reservoir systems operation (Bolouri-Yazdeli et al. 2014), water distribution systems monitoring (Bazargan-Lari 2014), site selection (Mahmoud 2014), and urban water systems (Motevallian et al. 2014). Despite the practicality of MCDMs in water-resources planning and management, the application of different MCDM techniques might yield different results. Therefore, providing a comparative multimethodological framework to choose among ranked solutions from MCDMs would be a valuable contribution. This study applies five MCDMs, namely (1) technique for order preference by similarity to ideal solution (TOPSIS), (2) modified-TOPSIS (M-TOPSIS), (3) compromise programming (CP), (4) complex proportional assessment (COPRAS), and (5) weighted aggregates sum product assessment (WASPAS). The MCDMs' solutions are ranked with the Borda aggregation method.

The optimal operation of the Karun4 reservoir in southwestern Iran is used as a case study in this work. Three criteria involving reliability, resiliency, and vulnerability constitute the objective functions of the MOOP. Due to robustness of the NSGA-II method in solving MOOPs, the paper implements this method with the aid of the *MATLAB* software. A comparative multimethodological framework is proposed to construct tradeoff curves and identify POS. The novelty of this paper is the employment of a framework involving multiple MCDMs in the identification of a compromise POS. This paper introduces COPRAS and WASPAS to multiobjective reservoir operation. The key objectives of this paper are (1) introducing theories related to the NSGA-II; (2) defining computational mechanisms of proposed MCDMs; (3) presenting simulation and optimization models for the Karun4 reservoir; (4) extracting the best Pareto frontier on the basis of the NSGA-II; (5) investigating a compromise POS for each MCDM; (6) aggregating the results via the Borda method; and (7) providing a comparison between robustness of the proposed MCDMs.

Material and Methods

The study area is first introduced in this section. The remainder of the section involves three parts: presenting the simulation-optimization model, describing the NSGA-II, and introducing the MCDMs (Fig. 1).

Case Study

This study addresses the optimal operation of the Karun4 reservoir with hydropower purposes with a monthly time scale over the period 1971–2000. Power plant capacity (PPC) of the hydropower system equals $1{,}000 \times 10^6$ W. The Karun4 reservoir is located in the semiarid region in the upper part of the Karun River, southwestern Iran. The mean annual precipitation and evaporation from the reservoir are 680 and 1,811.2 mm, respectively. The minimum and maximum reservoir storages equal $1{,}141 \times 10^6$ and $2{,}190 \times 10^6$ m^3, respectively.

Reservoir Operation: Simulation and Optimization Models

A reservoir system is simulated according to the continuity equation

$$S_{(t+1)} = S_{(t)} + Q_{(t)} - R_{(t)} - Sp_{(t)} - \mathrm{Loss}_{(t)} \quad \text{for } t = 1, 2, \ldots, T \tag{1}$$

where t = number of the operational period; $S_{(t)}$ and $S_{(t+1)}$ = the storages of reservoir, respectively, at the beginning and end of period t (MCM = 10^6 m^3); $Q_{(t)}$ = river inflow into the reservoir during period t (MCM); $R_{(t)}$ = release from the reservoir during period t (MCM); $Sp_{(t)}$ = overflow from the reservoir during period t (MCM); $\mathrm{Loss}_{(t)}$ = volume of evaporation loss from the reservoir during the period t (MCM); and T = number of operational periods (months).

The evaporation is calculated as follows:

$$\mathrm{Loss}_{(t)} = Ev_{(t)} \cdot \bar{A}_{(t)} \quad \text{for } t = 1, 2, \ldots, T$$
$$\bar{A}_{(t)} = \frac{A_{(t)} + A_{(t+1)}}{2} \tag{2}$$

where $Ev_{(t)}$ = evaporation from the reservoir surface during the period of t (m); $\bar{A}_{(t)}$ = average reservoir area during the period t (km^2); and $A_{(t)}$ and $A_{(t+1)}$ = reservoir areas respectively at the beginning and end of the period t (km^2). The area-storage formula is as follows:

$$A_{(t)} = a_1 S_{(t)}^3 + a_2 S_{(t)}^2 + a_3 S_{(t)} + a_4 \quad \text{for } t = 1, 2, \ldots, T \tag{3}$$

where a_1, a_2, a_3, and a_4 = constant coefficients of the area-storage equation.

The overflow from the reservoir is taken into account as follows:

$$SP_{(t)} = \begin{cases} 0 & \text{if } S_{(t+1)} \le S_{\max(t)} \\ S_{(t+1)} - S_{\max(t)} & \text{if } S_{(t+1)} > S_{\max(t)} \end{cases} \quad \text{for } t = 1, 2, \ldots, T \tag{4}$$

where $S_{\max(t)}$ = maximum reservoir storage during period t.

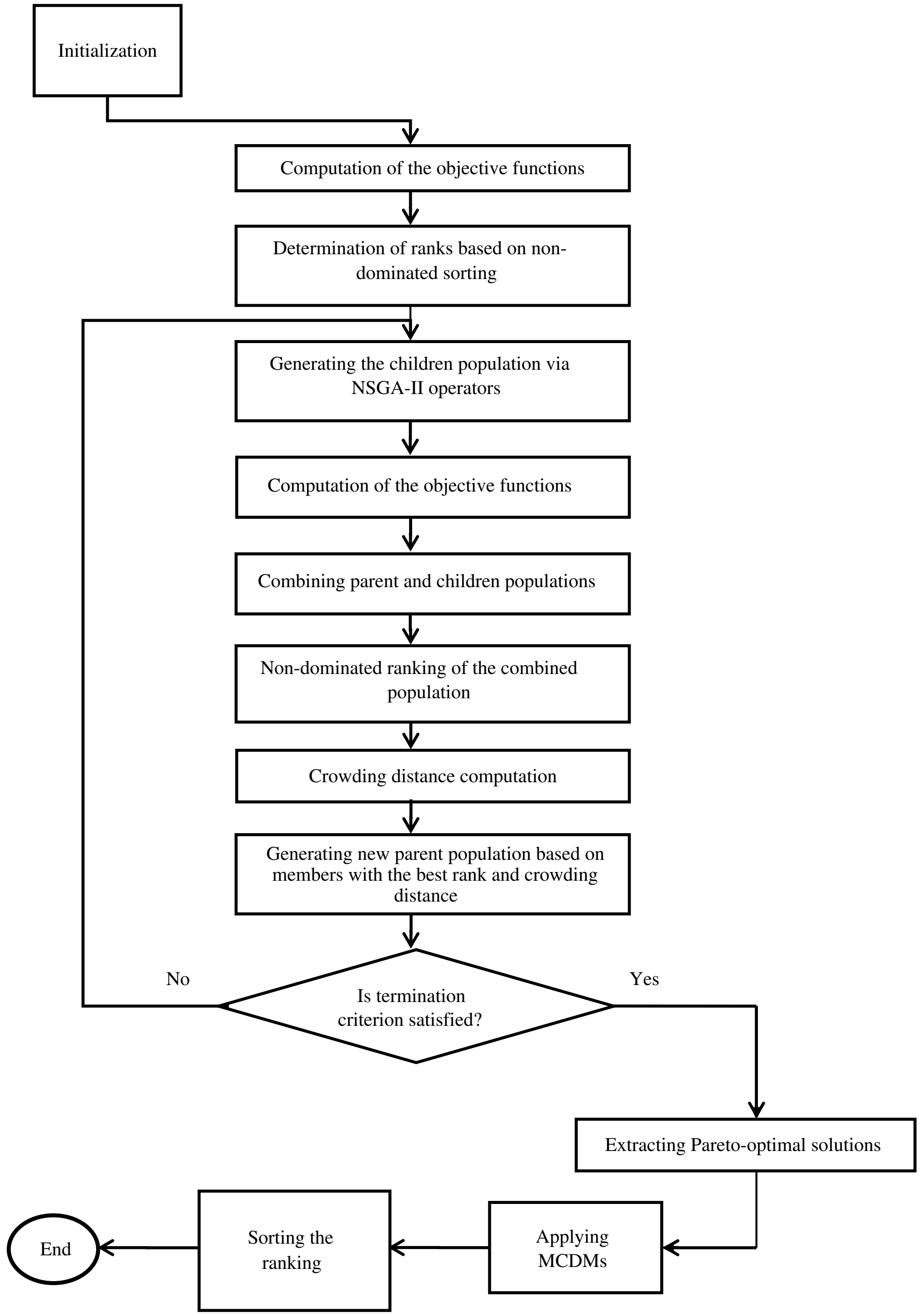

Fig. 1. Flowchart of the computational process

There are three constraints, one on releases [Eq. (5)], one on reservoir storage [Eq. (6)], and one on beginning and ending storage [the carry-over constraint, Eq. (7)]

$$R_{\min(t)} \leq R_{(t)} \leq R_{\max(t)} \quad \text{for } t = 1,2, \ldots, T \tag{5}$$

$$S_{\min(t)} \leq S_{(t)} \leq S_{\max(t)} \quad \text{for } t = 1,2, \ldots, T \tag{6}$$

$$S_{(1)} \leq S_{(T+1)} \tag{7}$$

where $R_{\min(t)}$ and $R_{\max(t)}$ = minimum and maximum allowable release from the reservoir during period t, respectively; $S_{\min(t)}$ = minimum storage in a period t; $S_{\max(t)}$ = maximum storage in period t; $S_{(1)}$ = initial reservoir storage; and $S_{(T+1)}$ = storage of the reservoir at the end of the operation period. Any water storage remaining in a reservoir at the end of the operational period is called carry-over water, which is credited to the next operational period (Colorado Division of Water Resources 2011).

Hydropower generation is calculated as follows:

$$P_{(t)} = \text{Min.}\left\{\left[\frac{g \times \eta \times Rp_{(t)}}{PF \times Mul_{(t)}}\right] \times \left[\frac{\frac{H_{(t)}+H_{(t+1)}}{2} - Tw_{(t)}}{1000}\right], \text{PPC}\right\} \quad \text{for} \quad t = 1, 2, \ldots, T \tag{8}$$

where $P_{(t)}$ = hydropower generation in period t (10^6 W); g = acceleration of gravity (m/s^2); η = efficiency of the power plant;

$Rp_{(t)}$ = water released from the power plant in period t (10^6 m^3); PF = plant functional coefficient; $\mathrm{Mul}_{(t)} = 10^6$ s in period t; H_t and H_{t+1} = reservoir water level at the beginning and end of period t (m), respectively; $Tw_{(t)}$ = reservoir tail-water level in period t (m); and PPC = power plant capacity. The storage-height formula is applied as follows:

$$H_{(t)} = b_1 S_{(t)}^3 + b_2 S_{(t)}^2 + b_3 S_{(t)} + b_4 \quad \text{for } t = 1, 2, \ldots, T \tag{9}$$

where b_1, b_2, b_3, and b_4 = constant coefficients of the storage-height equation.

Three objective functions must be optimized. Based on Hashimoto et al. (1982), the temporal reliability measures the number of periods during the operational period that generate power sufficient to meet the desired threshold. The resiliency measures the speed of recovery of a reservoir after a failure (the speed of rehabilitation). The vulnerability is the average number of failures/deficits during the operational period. The optimization objectives are then as follows:

Reliability is calculated as

$$\text{Maximize } z_1 = \frac{\mathop{N}\limits_{t=1}^{T} (P_t \geq \alpha \cdot \mathrm{PPC})}{T} \tag{10}$$

Resiliency is calculated as

$$\text{Maximize } z_2 = \frac{\mathop{N}\limits_{t=1}^{T-1} (P_t < \alpha \cdot \mathrm{PPC} | P_{t+1} \geq \alpha \cdot \mathrm{PPC})}{\mathop{N}\limits_{t=1}^{T} (P_t < \alpha \cdot \mathrm{PPC})} \tag{11}$$

Vulnerability is calculated as

$$\text{Minimize } z_3 = \frac{\sum_{t=1}^{T} (\alpha \cdot \mathrm{PPC} - P_t | P_t < \alpha \cdot \mathrm{PPC}, 0 | P_t \geq \alpha \cdot \mathrm{PPC})}{T} \tag{12}$$

where α = efficiency threshold of hydropower generation (here, $\alpha = 100\%$.); $\mathop{N}\limits_{t=1}^{T} (P_t \geq \alpha \cdot \mathrm{PPC})$ = number of periods that generated power is equal to or greater than $\alpha\%$ of the PPC; $\mathop{N}\limits_{t=1}^{T-1} (P_t < \alpha \cdot \mathrm{PPC} | P_{t+1} \geq \alpha \cdot \mathrm{PPC})$ = number of periods that it takes the system to recover from failure; $\mathop{N}\limits_{t=1}^{T} (P_t < \alpha \cdot \mathrm{PPC})$ = total failures in the operational period; and $\sum_{t=1}^{T} (\alpha \cdot \mathrm{PPC} - P_t | P_t < \alpha \cdot \mathrm{PPC}, 0 | P_t \geq \alpha \cdot \mathrm{PPC})$ = total deficits of generated power. The decision variables are the releases through the power plant.

Three following penalty functions are applied to penalize the infeasible solution unless the NSGA-II can solve the constraints separately:

$$P1 = K_1 [S_{(T+1)} - S_{(1)}]^2 \quad \text{if } S_{(T+1)} < S_{(1)} \tag{13}$$

$$P2_{(t)} = K_2 [S_{\min} - S_{(t+1)}]^2 \quad \text{if } S_{(t+1)} < S_{\min} \quad \text{for } t = 1, 2, \ldots, T \tag{14}$$

$$P3_{(t)} = K_3 [S_{(t+1)} - S_{\max}]^2 \quad \text{if } S_{(t+1)} > S_{\max} \quad \text{for } t = 1,2, \ldots, T \tag{15}$$

in which $P1$, $P2_{(t)}$, and $P3_{(t)}$ = penalty functions attributed to inequality of the storages of beginning and end of operation period,

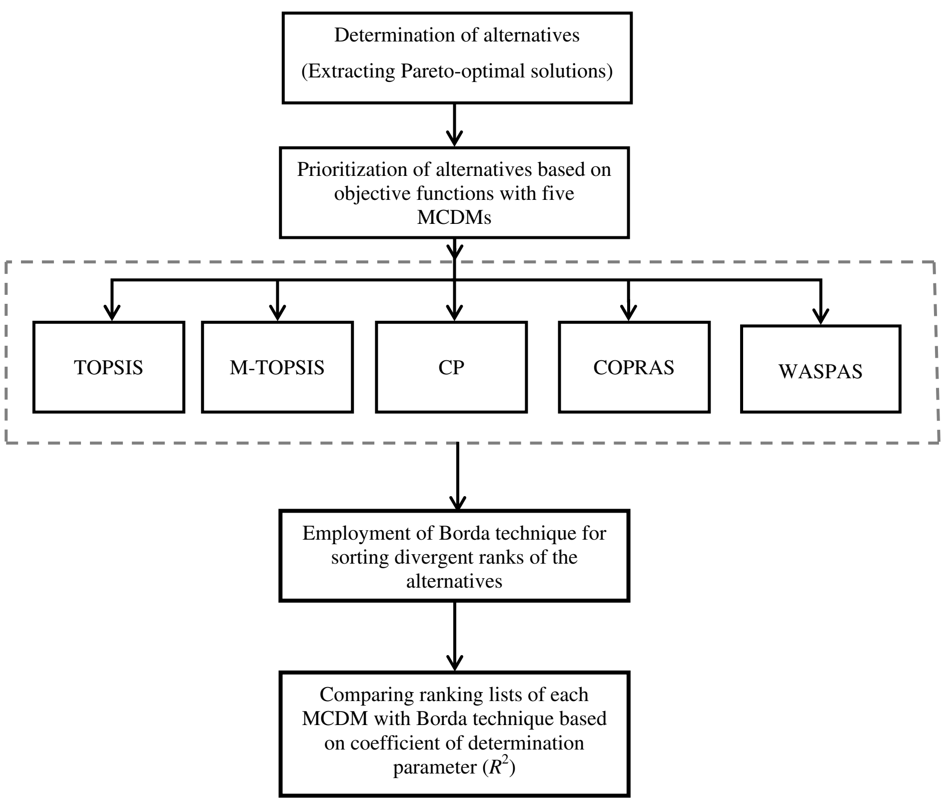

Fig. 2. Flowchart for the application of the MCDMs

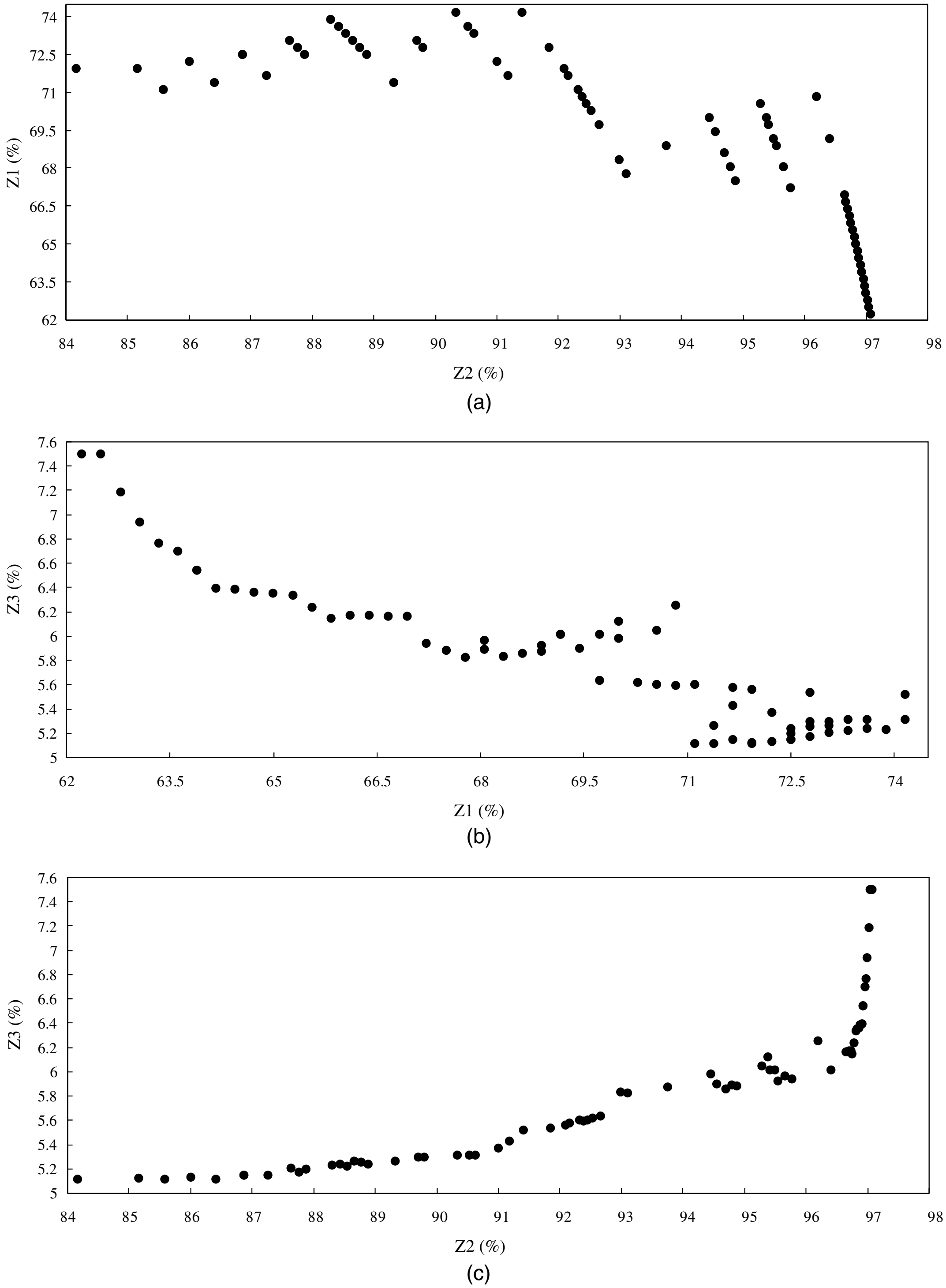

Fig. 3. Nondominated solutions generated by NSGA-II: (a) reliability versus resiliency; (b) reliability versus vulnerability; (c) resiliency versus vulnerability

reservoir storages less than minimum storage of reservoir, and reservoir storages more than maximum storage of reservoir, respectively; And K_1, K_2, and K_3 = the constants of the penalty function, which are considered 20, 30, and 30, respectively. Whenever the reservoir storage does not violate the constraints, the penalty functions will be zero.

The optimization objectives with consideration of the penalty functions are as follows:

Reliability is calculated as

$$\text{Maximize } Z_1 = z_1 - P1 - P2_{(t)} - P3_{(t)} \quad \text{for } t = 1, 2, \ldots, T \tag{16}$$

Resiliency is calculated as

$$\text{Maximize } Z_2 = z_2 - P1 - P2_{(t)} - P3_{(t)} \quad \text{for } t = 1,2, \ldots, T \tag{17}$$

Table 1. Ranks of Each POS Calculated with the Proposed MCDMs

Alternative	TOPSIS	M-TOPSIS	CP_1	CP_2	CP_∞	WASPAS	COPRAS
POS1	8	4	2	3	16	6	2
POS2	50	56	29	30	34	59	47
POS3	66	66	44	54	59	66	63
POS4	65	65	40	47	51	65	60
POS5	54	53	23	43	49	60	45
POS6	63	61	36	48	53	63	57
POS7	55	55	24	42	48	61	49
POS8	43	54	52	40	29	56	52
POS9	56	52	65	65	62	45	59
POS10	51	47	62	61	58	42	54
POS11	5	2	22	21	13	3	4
POS12	1	1	18	19	22	1	1
POS13	32	19	51	46	40	17	32
POS14	70	70	56	62	69	70	70
POS15	29	21	43	39	33	23	29
POS16	30	17	48	45	36	14	27
POS17	28	41	35	17	6	39	35
POS18	52	49	63	63	60	43	55
POS19	45	38	59	57	52	32	46
POS20	2	3	20	10	10	2	3
POS21	42	43	12	35	41	54	36
POS22	34	33	9	24	31	47	26
POS23	49	45	61	60	56	38	53
POS24	60	60	68	68	67	46	64
POS25	31	34	45	36	30	35	39
POS26	59	59	67	67	66	49	62
POS27	35	22	53	50	43	21	37
POS28	39	35	58	55	50	29	44
POS29	41	40	11	37	42	53	33
POS30	19	9	1	14	28	15	6
POS31	18	31	25	9	2	31	25
POS32	57	58	27	41	46	62	51
POS33	17	23	38	26	20	20	22
POS34	48	42	60	59	55	36	50
POS35	26	27	41	28	26	26	31
POS36	33	30	6	25	32	41	21
POS37	40	39	8	38	44	52	30
POS38	58	57	66	66	64	50	61
POS39	62	64	70	70	69	48	67
POS40	11	16	34	18	11	11	16
POS41	61	63	69	69	68	40	66
POS42	22	36	28	13	1	34	28
POS43	3	5	31	20	15	4	5
POS44	37	51	49	33	23	51	48
POS45	52	49	63	63	60	43	55
POS46	24	37	42	27	17	30	34
POS47	16	15	39	29	26	13	19
POS48	38	29	57	53	47	27	43
POS49	14	24	19	5	5	24	18
POS50	6	11	32	15	3	8	14
POS51	20	12	3	11	25	19	9
POS52	25	32	14	12	19	37	24
POS53	9	10	5	1	12	10	8
POS54	68	68	50	58	65	68	68
POS55	23	26	7	7	21	33	17
POS56	27	13	47	44	35	12	23
POS57	12	18	10	2	9	16	13
POS58	10	8	30	22	17	9	12
POS59	69	69	54	56	63	69	69
POS60	13	20	13	4	8	18	15
POS61	36	25	55	51	45	25	40
POS62	21	14	4	8	24	22	10
POS63	63	61	36	48	53	63	57
POS64	15	28	21	6	4	28	20
POS65	67	67	46	52	57	67	65
POS66	47	48	17	31	37	58	42
POS67	44	44	15	34	39	55	38
POS68	7	7	33	23	13	7	11
POS69	46	46	16	32	38	57	41
POS70	4	6	26	16	7	5	7

Vulnerability is calculated as

$$\text{Minimize } Z_3 = z_3 + P1 + P2_{(t)} + P3_{(t)} \quad \text{for } t = 1, 2, \ldots, T \tag{18}$$

NSGA-II

The NSGA-II relies on such features as crowding distance, binary tournament selection, and elitist nondominated sorting to choose the best nondominated solutions through a step-by-step procedure. Based on Deb et al. (2002), the computational process is started by initialization of the population/chromosome, where the chromosomes are possible solutions to the problem at hand. The decision variables as well as objective functions are evaluated through simulation including selection, crossover, and mutation operations.

Different nondominated fronts of the population of solutions are extracted on the basis of the non-dominated sorting concept. Once the first Pareto front is extracted, the population is again ranked and each nondominated front is assigned a rank or level. The nondominated front that is assigned the first rank is the optimal Pareto of the current population. Then, the solutions are sorted regarding nondominated fronts in ascending order. The population members (that is, solutions) who have higher ranks are removed and the others become candidates for generating the parent population of the next generation (children population).

Thereafter, the crowding distance of a particular solution is evaluated for each objective function. The crowding distance is the average distance of its two neighboring solutions. The solutions of each level are sorted with respect to crowding distance in descending order.

In the next step, which is called the selection step, the binary tournament selection operator is applied, whereby among two randomly chosen solutions from the population, a solution with lower rank and greater crowding distance is selected. Similar to the size of the parent population, the children population is generated by repeating the selection operator along with the employment of the crossover and mutation operators. After performing the simulation process to evaluate the objective functions, nondominated sorting is used for the combination of parent and children populations. During the last step, which is called elitism, the optimal solutions of each generation construct a new parent population. After satisfying the termination criteria, the solutions of the last generation are considered an optimal Pareto frontier. Supplementary information is presented in Deb et al. (2002).

MATLAB 7.11.0 was used to implement the NSGA-II for simulation and optimization using the aforementioned equations. The crossover rate, mutation rate, population size, and number of generations of the NSGA-II were determined by trial and error.

MCDMs

After extracting the Pareto frontier based on instructions of the two previous subsections, the most appropriate POS is recognized via MCDMs. Considering $X = [x_{ij}]_{mn}$ as a decision matrix, x_{ij} denotes preference of alternative i with respect to criterion j. All the

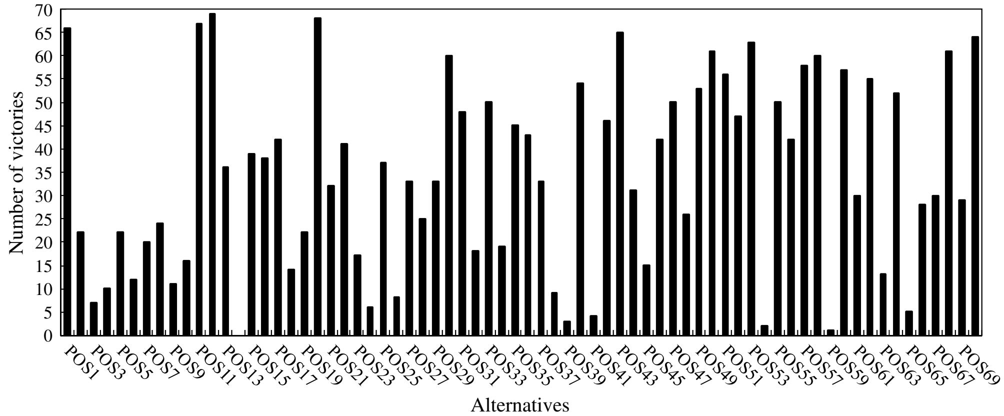

Fig. 4. Number of victories for each POS within Borda contests

MCDMs implement the three following steps: (1) determination of appropriate criteria and alternatives, (2) assignment of weight to the evaluation criteria, and (3) prioritization of alternatives according to satisfying evaluation criteria. In addition, the elements of the decision matrix are normalized. Moreover, the weights of the evaluation criteria (w_j) are considered equal to each other in the present study.

The five implemented MCDMs prioritize the POSs with respect to each objective function to single out the compromise solution. The implemented MCDMs make different assumptions. The CP emphasizes the distance from the ideal point while TOPSIS and M-TOPSIS consider quantified proximity to an ideal solution along with distance from a negative-ideal solution. COPRAS' prioritization is on the basis of separated evaluation of maximizing and minimizing criteria whereas WASPAS applies combination of summation and multiplication. In general the MCDMs yield divergent rankings. Thus, the next step is to sort (aggregate) the ranks from the MCDMs with the Borda technique. The proposed method sorts the ranks on the basis of victories in pairwise contests. Moreover, the coefficient of determination (R^2) is used to compare resemblance of MCDMs' ranks to the Borda ranks. The computational algorithm of the proposed method is depicted in Fig. 2. The formulas used by the MCDMs are as follows.

In CP, the best solution among a set of solutions has the least distance from the ideal point as follows (Zeleny 1973):

$$L_p(\mathrm{POS}_i) = \left[\sum_{j=1}^{n}\left(\frac{x_j^+ - x_{ij}}{x_j^+ - x_j^-}\right)^p\right]^{1/p} \tag{19}$$

where $L_p(\mathrm{POS}_i)$ = distance of a POS to the ideal solution; x_j^+ and x_j^- = respectively the ideal solution (largest value for maximizing criteria or smallest value for minimizing criteria) and negative-ideal solution (largest value for minimizing criteria or smallest value for maximizing criteria). Three values of the p parameter are used to evaluate L_p. The distances evaluated on the basis of $p = 1$, $p = 2$, and $p = \infty$ are called Block distance, Euclidean distance, and Tchebycheff distance, respectively (Pomerol and Barba-Romero 2000).

The TOPSIS technique prioritizes alternatives according to the quantified proximity to an ideal solution (D_j^+) along with distance from a negative-ideal solution (D_j^-) as follows (Hwang and Yoon 1981):

$$D_j^+ = \sqrt{\sum_{j=1}^{n}(x_{ij} - x_j^+)^2} \tag{20}$$

$$D_j^- = \sqrt{\sum_{j=1}^{n}(x_{ij} - x_j^-)^2} \tag{21}$$

$$C_j^* = \frac{D_j^-}{D_j^+ + D_j^-} \tag{22}$$

in which, the solutions are ranked based on the descending value of the similarity ratio (C_j^*).

M-TOPSIS was developed by Ren et al. (2007) to avoid rank reversals and occasional evaluation failure encountered in TOPSIS. This technique uses R_j^* rather than C_j^*, which is ranked in increasing order as follows:

$$R_j^* = \sqrt{[D_j^+ - \min(D_j^+)]^2 + [D_j^- - \max(D_j^-)]^2} \tag{23}$$

In COPRAS, maximizing and minimizing evaluation criteria are calculated separately within the computational process as follows (Zavadskas et al. 1994):

$$S_j^+ = \sum_{Z_i=+} x_{ij} \tag{24}$$

$$S_j^- = \sum_{Z_i=-} x_{ij} \tag{25}$$

$$Q_j = S_j^+ + \frac{S_{\min}^- \sum_{j=1}^{n} S_j^-}{S_j^- \sum_{j=1}^{n} \frac{S_{\min}^-}{S_j^-}} \tag{26}$$

where S_j^+ and S_j^- = sum of the maximizing and minimizing criteria, respectively. The minimum value of S_j^- is presented by $S_{\min}^-$.

The degree of the alternatives' utilities, which vary from 0 to 100% between the worst and the best alternatives, is obtained as follows:

$$N_j = \frac{Q_j}{Q_{\max}} \times 100 \tag{27}$$

WASPAS was introduced by Zavadskas et al. (2012) and developed by integration of the weighted sum model (WSM) and weighted product model (WPM) as follows:

Table 2. Final Ranks of POSs Obtained with the Borda Aggregation Technique

Alternative	Rank
POS1	4
POS2	47
POS3	63
POS4	60
POS5	47
POS6	58
POS7	50
POS8	46
POS9	59
POS10	54
POS11	3
POS12	1
POS13	34
POS14	70
POS15	31
POS16	32
POS17	27
POS18	56
POS19	47
POS20	2
POS21	38
POS22	30
POS23	53
POS24	64
POS25	33
POS26	62
POS27	35
POS28	45
POS29	35
POS30	10
POS31	22
POS32	52
POS33	19
POS34	51
POS35	25
POS36	26
POS37	35
POS38	61
POS39	67
POS40	16
POS41	66
POS42	24
POS43	5
POS44	39
POS45	55
POS46	27
POS47	19
POS48	44
POS49	17
POS50	8
POS51	14
POS52	23
POS53	7
POS54	68
POS55	19
POS56	27
POS57	12
POS58	10
POS59	69
POS60	13
POS61	40
POS62	15
POS63	57
POS64	18
POS65	65
POS66	43
POS67	40
POS68	8
POS69	42
POS70	6

$$A_j = \lambda \sum_{j=1}^{n} x_{ij} + (1-\lambda) \prod_{j=1}^{n} (x_{ij}) \tag{28}$$

where $\lambda = \{0, 0.1, 0.2, \ldots, 1\}$ yet most researchers set $\lambda = 0.5$. The solutions were ranked based on the descending values of A_j.

The Borda technique is used for the sorting of the rankings generated by the aforementioned MCDMs. This technique conducts pairwise comparisons among ranked alternatives in each MCDM to determine the final ranking list. Considering m as the total number of alternatives, the first priority belongs to the alternative or POS that gains more victories in $m \times m - 1/2$ contests (de Borda 1781).

Results and Discussion

The NSGA-II toolbox of *MATLAB* was used to extract the POSs. The crossover rate, mutation rate, population size, and number of generations were determined by trial and error to equal 0.65 (via two-point crossover function), 0.05 (via uniform function), 200, and 10,000, respectively. Moreover, the selection process involved a roulette wheel.

Owing to the fact that showing 70 extracted POSs of the three objective functions would be unworkable, the Pareto frontier figure was decomposed into three separated graphs (Fig. 3). According to the results emerging from Fig. 3, the maximum percent of reliability (Z_1), and resiliency (Z_2), were computed as 74.17 and 97.06%, respectively. Meanwhile, the minimum values attributed to Z_1 and Z_2 were respectively evaluated as 62.22 and 84.16%. The ideal and negative-ideal values of vulnerability (Z_3) varied between 5.11 and 7.50%, respectively.

The next step is providing priority lists for the 70 extracted POSs with aid of the MCDMs. Table 1 lists the ranks of each POS with respect to the five applied MCDMs. Due to the fact that the p parameter in the CP method influences the ranking of alternatives, three values of p representing the Block, Euclidean, and Tchebycheff distances were used. A glance at the ranking list reveals the fact that there is diversity among the prioritization of the POSs. The results highlight the fact that selection of a robust MCDM is a challenging issue. Which ranking list would one choose? Yilmaz and Harmancioglu (2010) and Banihabib et al. (2015) designed a multimethodological framework involving various MCDMs to answer this question. They selected the best MCDM on the basis of the performance of MCDMs in sensitivity analysis. This approach, however, would not be practical for researches that consider weights of the evaluation criteria that are equal to each other. Therefore, this study applied the Borda technique to obtain the final ranking. The prioritization of the POSs on the basis of the number of victories in pairwise contests involved $70 \times 69/2 = 2415$ contests held. Fig. 4 and Table 2 show the number of victories by each POS, and the ranks of each POS obtained with the Borda method, respectively. The optimal releases, storage, and generated power during the operation period of the Karun4

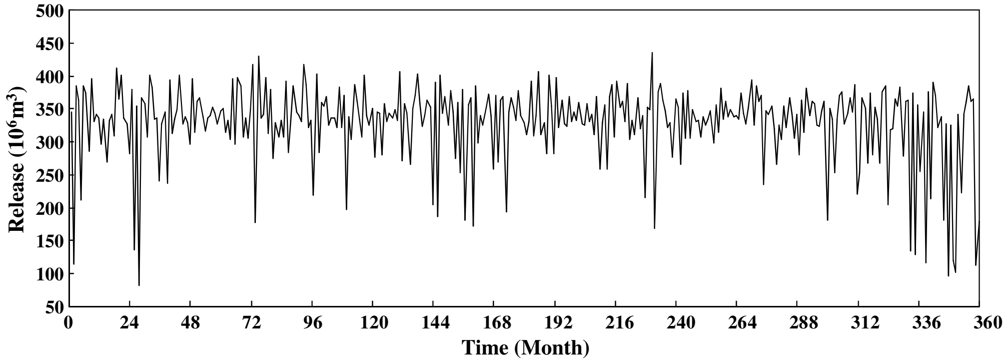

Fig. 5. Optimal release during the operation period of the Karun4 reservoir

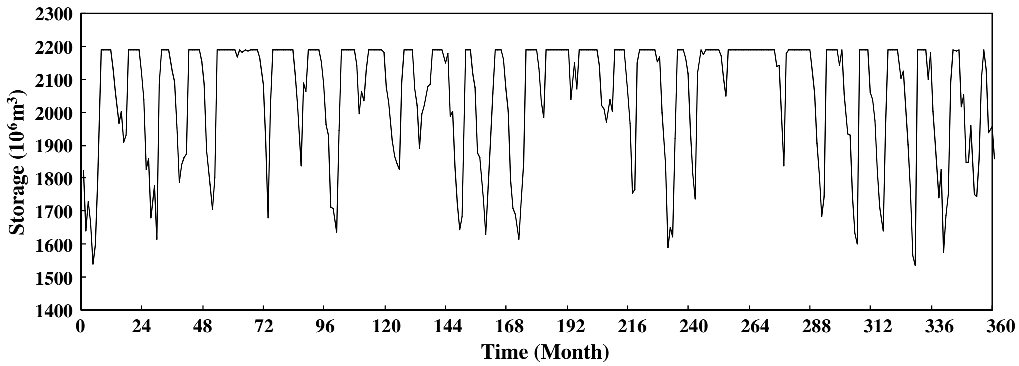

Fig. 6. Optimal storage during the operation period of the Karun4 reservoir

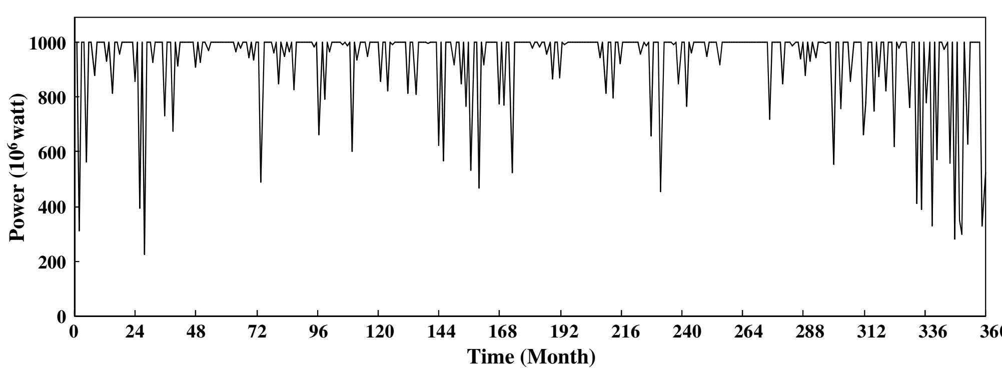

Fig. 7. Optimal generated power during the operation period of the Karun4 reservoir

reservoir according to POS12's results, which were the first priority of the Borda method, are presented in Figs. 5–7. The POS12 was also chosen as the first priority by the TOPSIS, M-TOPSIS, WASPAS, and COPRAS techniques due to its values equal to 0.944, 0, 0.888, and 1 for C^*, R^*, A_j, and N_j, respectively.

The last computational step was the assessment of the MCDMs' performance with respect to similarity of their rankings to the Borda method. Based on results of R^2 in Fig. 8, the highest and lowest similarity belongs to COPRAS and CP ($p = 1$), respectively. COPRAS has proven its practicality in various researches; however, there is only one reported publication of its utilization in water-resources management (Azarnivand and Chitsaz 2015). Based on the results of the current study, the modified version of TOPSIS was not as successful as the classical TOPSIS. Moreover, despite the capabilities and successful application of the CP in previous works, it did not perform well in this case. These facts are in line with the findings by Mergias et al. (2007), who emphasized that there are no all-around best or worst MCDMs; rather, their performances vary with particular decision-making problems.

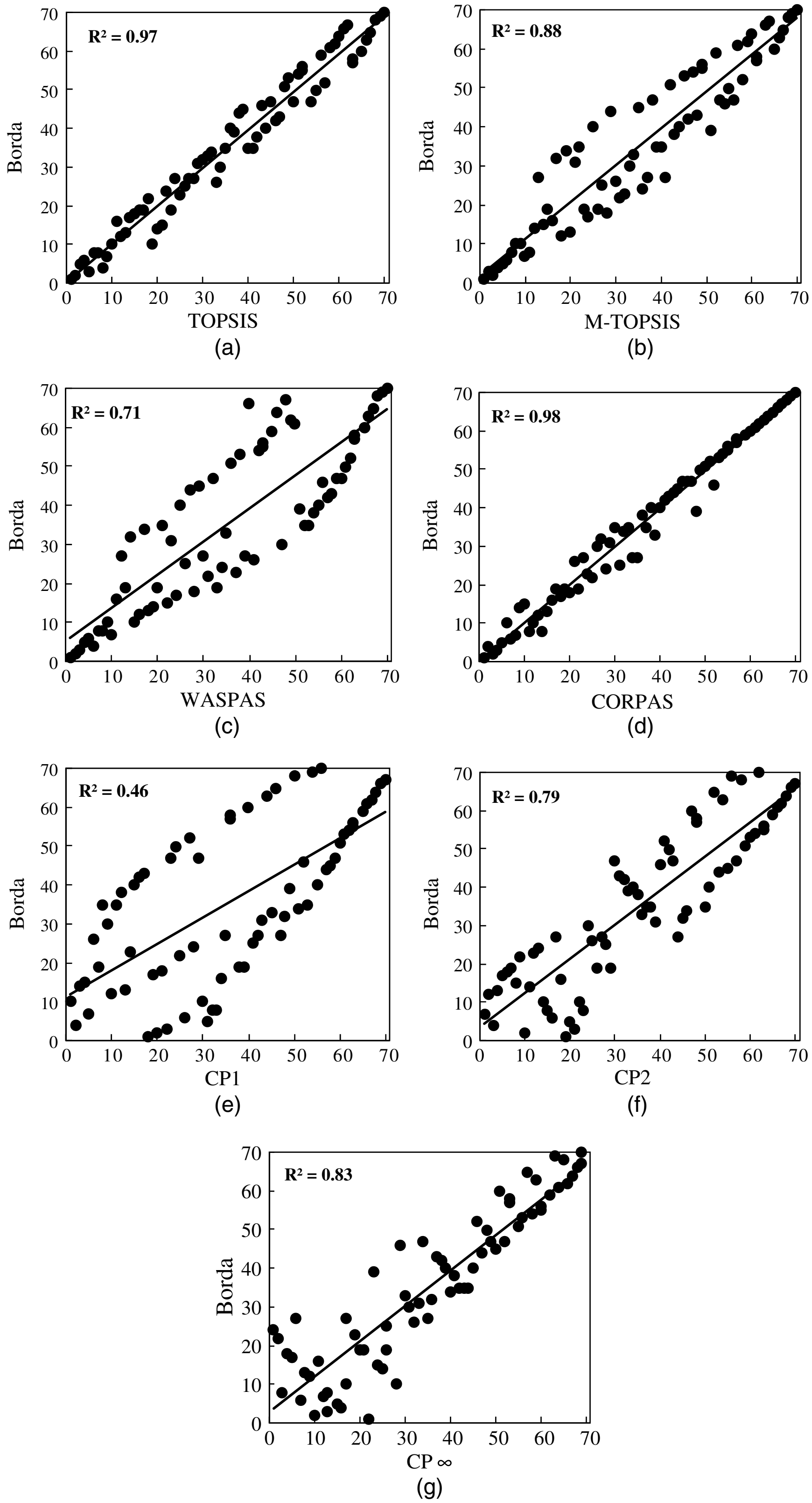

Fig. 8. Regression of utilized MCDMs' ranking lists with Borda results based on the coefficient of determination (R^2): (a) TOPSIS versus Borda; (b) M-TOPSIS versus Borda; (c) WASPAS versus Borda; (d) COPRAS versus Borda; (e) CP_1 versus Borda; (f) CP_2 versus Borda; (g) CP_∞ versus Borda

Concluding Remarks

The current research obtained a Pareto optimal solution to a MOOP regarding the Karun4's reservoir operation. Three performance criteria, namely reliability, resiliency, and vulnerability, constituted the objective functions of the problem. The computational model consisted of two stages. The first stage was the implementation of a reservoir simulation-optimization model using the NSGA-II. The second stage, unlike previous studies, implemented a comparative MCDM analysis to extract the best ranked Pareto optimal solution of the reservoir-operation problem. Most previous works have not searched for the best ranking of solutions obtained from MCDMs.

The NSGA-II calculated 70 nondominated solutions that present a wide variety of policies for decision-makers. The ideal percent of reliability, resiliency, and vulnerability were computed to be equal to 74.17, 97.06, and 5.11%, respectively. Then, a set of MCDMs were applied to single out an overall nondominated solution. The reason why a set of MCDMs was used instead of one MCDM is rooted in the different assumptions made by the MCDMs that resulted in divergent prioritization lists. The Borda technique was applied to overcome such divergence of results from the MCDMs, which provided two benefits: (1) it could sort divergent results of the five utilized MCDMs; and (2) it provided a mechanism to compare the efficiencies of the applied MCDMs.

Among the applied MCDMs, COPRAS, which has received little attention by water-resources researchers, showed the highest similarity of sorted ranks. Thus, it might be useful for water-resources researchers to apply recently developed MCDMs, such as COPRAS, in their future research. The R^2 value of COPRAS-Borda was equal to 0.98, which is approximately two times larger than that of CP_1-Borda. TOPSIS also performed well, and it was superior to the modified TOPSIS.

In summary, this paper's results emphasized the necessity of resorting to practical multimethodological evaluation to make robust decisions leading to an overall POS. Future work will focus on the testing and implementation of other MCDMs and aggregation methods for optimal multiobjective decision-making problems.

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