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Optimal Reservoir Operation Using Multi-Objective Evolutionary Algorithm

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Abstract. This paper presents a Multi-objective Evolutionary Algorithm (MOEA) to derive a set of optimal operation policies for a multipurpose reservoir system. One of the main goals in multi-objective optimization is to find a set of well distributed optimal solutions along the Pareto front. Classical optimization methods often fail in attaining a good Pareto front. To overcome the drawbacks faced by the classical methods for Multi-objective Optimization Problems (MOOP), this study employs a population based search evolutionary algorithm namely Multi-objective Genetic Algorithm (MOGA) to generate a Pareto optimal set. The MOGA approach is applied to a realistic reservoir system, namely Bhadra Reservoir system, in India. The reservoir serves multiple purposes irrigation, hydropower generation and downstream water quality requirements. The results obtained using the proposed evolutionary algorithm is able to offer many alternative policies for the reservoir operator, giving flexibility to choose the best out of them. This study demonstrates the usefulness of MOGA for a real life multi-objective optimization problem.

Key words: multi-objective optimization, Genetic Algorithms, reservoir operation, Pareto front, irrigation, hydropower

1. Introduction

In real life, most of the water resources optimization problems involve conflicting objectives, for which there is no efficient method for finding multiple trade-off optimal solutions. Most of the reservoir systems serve multiple purposes and they are multi-objective in nature. To optimize such a complex reservoir system, the dynamic programming (DP), linear programming (LP) and non-linear programming (NLP) have been widely applied in the past (Yeh, 1985). However, when DP is applied to a multi-reservoir system, it involves a major problem of the curse of dimensionality, with increase in the number of state variables. The techniques like LP and NLP have essential approximation problems in dealing with discontinuous, non-differentiable, non-convex multi-objective functions. Recently, there has been an increasing interest in biologically motivated adaptive systems, for solving optimization problems. The Genetic Algorithms (GAs) are one of the most promising techniques in natural adaptive system field of Evolutionary Algorithm (EA) paradigm and are receiving wide attention, because of their flexibility and effectiveness for optimizing complex systems. Genetic Algorithms use a population of solutions in each iteration, instead of a single solution and so they are called population-based approaches (Goldberg, 1989). This is one of the most striking differences between classical optimization methods and GAs. GAs use objective function information directly, and do not require its derivatives or any other auxiliary information. Sometimes this may lead to slower convergence, as it is not explicitly using derivative information. GAs use randomized initialization and stochastic algorithm in their operation, so they can locate the search at any place in the search space, and can overcome the problems of local optima. GAs are found to be suitable for solving reservoir operation problems (Oliveira and Loucks, 1997; Wardlaw and Sharif, 1999; Sharif and Wardlaw, 2000). GAs are not restricted by the number of dimensions as computer memory requirement increases only linearly, but not exponentially on increase in dimensions. The classical optimization methods such as DP, LP, and NLP are not appropriate to multi-objective optimization, because these methods use a point-by-point search approach, and the outcome for which is a single optimal solution. Most of the classical optimization methods consider multiple objective functions, using weighted approach or constrained approach, without considering all the objectives simultaneously. Optimization of any multi-purpose reservoir system is to solve multi-dimensional multi-objective problems. The multimember approach, followed in Evolutionary Algorithms (EA), makes them an ideal processor that can be used for solving multi-objective optimization problems (Deb, 2001).

In this paper, it is intended to apply a Multi-objective Evolutionary algorithm (MOEA) to a multipurpose reservoir operation problem. The results obtained show the effectiveness of MOEAs for deriving optimal policies for multi-objective reservoir operation. In the following sections, a brief introduction of multi-objective optimization and MOEAs is presented. Then details of the case study and the model formulated for reservoir operation are explained. Finally the results are discussed, followed by the conclusion.

2. Multi-Objective Optimization

Multi-objective optimization problems represent an important class of real-world optimization problems. Typically such problems involve trade-offs. For example, in the case of a multipurpose reservoir, which mainly serves hydropower and irrigation as key purposes, the reservoir operator may wish to maximize benefits from hydropower generation, while releasing sufficient water for irrigation to meet the demands. These objectives are typically conflicting with each other. A higher profit from hydropower generation would decrease the irrigation releases. There is no single optimal solution. Often the reservoir operator needs to consider many possible "trade-off" solutions before choosing the one that best suits his need. The curve or surface (for more than 2 objectives), describing the optimal trade-off solutions between the objectives, is known as the Pareto front.

Pareto optimum concept, also known as the non-inferior solution, is fundamental to multi-objective analysis (Haimes *et al.*, 1990). Qualitatively, a non-inferior solution of a multi-objective problem is one, in which any improvement of one objective function can be achieved only at the expense of another. In general, there are three ways of specifying a noninferior solution (Haimes *et al.*, 1990), viz., by the values of its decision variables, $x_1, \ldots, x_n$; by the trade-off functions $\lambda_{i1}, \ldots, \lambda_{in}$ and by its objective function values $f_1, \ldots, f_n$. The first approach is generally ruled out, due to inefficiencies of decision space manipulations. The second approach may involve difficulties, when discontinuities or nonconvexities occur in the functional space, but can be useful in some other cases. The third approach with objective function space is the best way to define noninferior solution set and is therefore used in this study.

To define a noninferior solution mathematically, consider the following multi-objective function problem, also known as a vector optimization problem:

$$\min_{x \in X}\{f_1(x),\ f_2(x), \ldots, f_n(x)\} \tag{1}$$

where, $f_1, f_2, \ldots, f_n$ are objective function values; x is N-dimensional vector of decision variables; X is the set of all feasible solutions $= \{x/g_i(x) \leq 0;\ i = 1, 2, \ldots, m\}$.

DEFINITION 1. A decision x^* is said to be a non-inferior solution to the multi-objective problem given in (1), if and only if there does not exist another $\bar{x}$ so that $f_j(\bar{x}) \leq f_j(x^*)$, $j = 1, 2, \ldots, n$, with strict inequality holding for at least one j.

Numerous methods exist for solving multi-objective problems. They include utility functions, indifference functions, the lexicographic approach, parametric approach or weighted approach, ε-constraint approach, goal programming approach, goal attainment method, adaptive search method, interactive approaches, ELECTRE method, the surrogate worth trade-off method etc. (Loucks *et al.*, 1981; Goicoechea *et al.*, 1982; Haimes *et al.*,1990). Tauxe *et al.* (1979) have applied a multi-objective dynamic programming model for analyzing a reservoir operation problem, involving three conflicting objectives. Thampapillai and Sinden (1979), Mohan and Raipure (1992) analyzed the tradeoffs for multiple objective planning through linear programming. Raj and Kumar (1996) used ELECTRE method for ranking of river basin planning alternatives in a multi criterion environment. Various solution techniques to handle multiple objectives have been reviewed by Cohon and Marks (1975) and categorized them into two types; viz., generating techniques, which completely identify the noninferior set, and other techniques, which are based on articulation of preferences, apriori or progressively, during the analysis.

In the past, to handle multi-objective optimization problems of reservoir operation, weighted approach and constraint methods were used by many of the researchers. In the constraint method, all objectives except one are constrained to specific values. The remaining objective is then optimized, yielding a Pareto optimal solution. This is often referred as ε-constraint approach and a priori estimates of objective worth are thereby eliminated. The values of the constraints are incremented, and the model is run again to find another Pareto point. These steps are repeated until the tradeoff relationship is sufficiently represented. In the weighting method, all the design objectives are given weights and are considered in the objective function simultaneously. A different set of weights is used in each run of the optimization model.

Various researchers have used constraint method for generation of noninferior set and trade-off curves for reservoir operation problems (Croley and Rao, 1979; Liang *et al.*, 1996 and Yeh and Becker, 1982). Cohon and Marks (1973) have used both those approaches for multi-objective analysis and reported that weighting method fails, when noninferior set is not convex, but constraint method is able to generate the entire noninferior set. Unlike the constraint method, the weighting method cannot identify concavities in the Pareto set. Also, many combinations of weights may lead to the same Pareto solution, resulting in wastage of computational time. Furthermore these methods require many trials to generate the nondominated solutions. Thus classical methods have some drawbacks and to overcome them multi-objective evolutionary algorithms have been proposed (Deb, 2001).

2.1. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHMS

Multi-objective evolutionary algorithms use a population-based search, and are attractive as they find many Pareto optimal solutions in a single run. Multi-objective GAs, which have many attractive features for real life water resource systems optimization, have had only limited applications so far. The present work focuses on application of multi-objective GAs to multi-purpose reservoir operation optimization.

The inherent parallel structure of a GA provides some important advantages in multi-objective (MO) analysis. If the plain aggregation methods are used in GAs, it will work similar to classical MO procedures for optimization. These methodologies do not take advantage of the GA's population-based search, to generate the Pareto set in a single run, instead of requiring a number of iterations. To overcome such contingencies, Pareto-based approaches were proposed by Goldberg (1989) and these have acquired major focus in MOGA research. The solutions of multi-objective GAs yield a trade-off curve or surface, identifying a population of points that define optimal solutions of the problem on hand. During the last decade, a number of EAs were suggested to solve multi-objective optimization problems. Of them Non-dominated Sorting Genetic Algorithm (NSGA) (Srinivas and Deb, 1994), Niched Pareto Genetic Algorithm (NPGA) (Horn *et al.,* 1994) have received good recognition. Cieniawski *et al.* (1995) and Ritzel *et al.* (1994) were among the earlier applications of MOEAs in water resources management. An important advantage of Pareto approaches is that they are able to identify solutions in concave areas of the Pareto set. A brief overview of MOEAs can be found in Fonseca and Fleming (1995) and comparison of various MOEAs is presented in Zitzler *et al.* (2000). A detailed description of Multi-Objective Optimization using Evolutionary Algorithms is given in Deb (2001).

Recently elitist multi-objective evolutionary algorithms were found more efficient than those without elitism, since the elitism helps to preserve the best solutions in the past iterations and speeds up the convergence of the solution. Of them, Pareto-Archived Evolution Strategy (PAES; Knowles and Corne, 1999), Strength-Pareto Evolutionary Algorithm (SPEA; Zitzler and Thiele, 1999) and Non-dominated Sorting Genetic Algorithm-II (NSGA-II; Deb *et al.,* 2002) are popular due to their efficiency in producing better Pareto front. Deb *et al.* (2002) showed that NSGA-II outperforms PAES and SPEA in terms of finding a diverse set of solutions and in converging nearer to the true Pareto-optimal set.

The present study uses NSGA-II principle to apply MOGA for reservoir operation problem. The procedure of NSGA-II provides an efficient sorting scheme for classifying the population into different fronts and a good diversity preserving mechanism for non-dominated solutions in the population. In MOGA method, first the population is initialized within the specified variable ranges. After evaluation of this population, based on non-dominated sorting approach, the generated alternatives are classified into different fronts. The population members are ranked according to their fitness values (f_{rank}) and are selected for genetic operation, on a pair-wise comparison to produce an offspring in the generation. In this selection process, if any pair is having the same rank, then the crowded distance values (f_{dist}) calculated using crowding distance assignment operator (Deb *et al.*, 2002) provides basis and helps to maintain diversity in the population. To change the attributes of the offspring, crossover and mutation operations were performed. The procedure is repeated for a pre-specified number of generations, with the goal of achieving diverse set of non-dominated solutions, possibly attaining true Pareto optimal solutions. To preserve the best solutions obtained through generations and to speed up the convergence, the algorithm uses elitism, in which the combination of parents and offspring population are grouped into different fronts and the best individuals selected for the next generation. Figure 1 shows the flowchart of Multi-objective Genetic Algorithm. In this study chromosomes are coded by real values.

To handle the constraints in MOGA, the natural self-adaptation mechanism of the evolutionary algorithms is useful to bias the search through a constrained space. For this purpose three criteria are used to select the best individuals from a generation (Deb *et al.*, 2002). (i) Out of two feasible solutions, the one with better fitness value is preferred. (ii) If one solution is feasible and the other one is infeasible, the feasible one is preferred. (iii) If both solutions are infeasible, the one with the lowest sum of constraint violations is preferred.

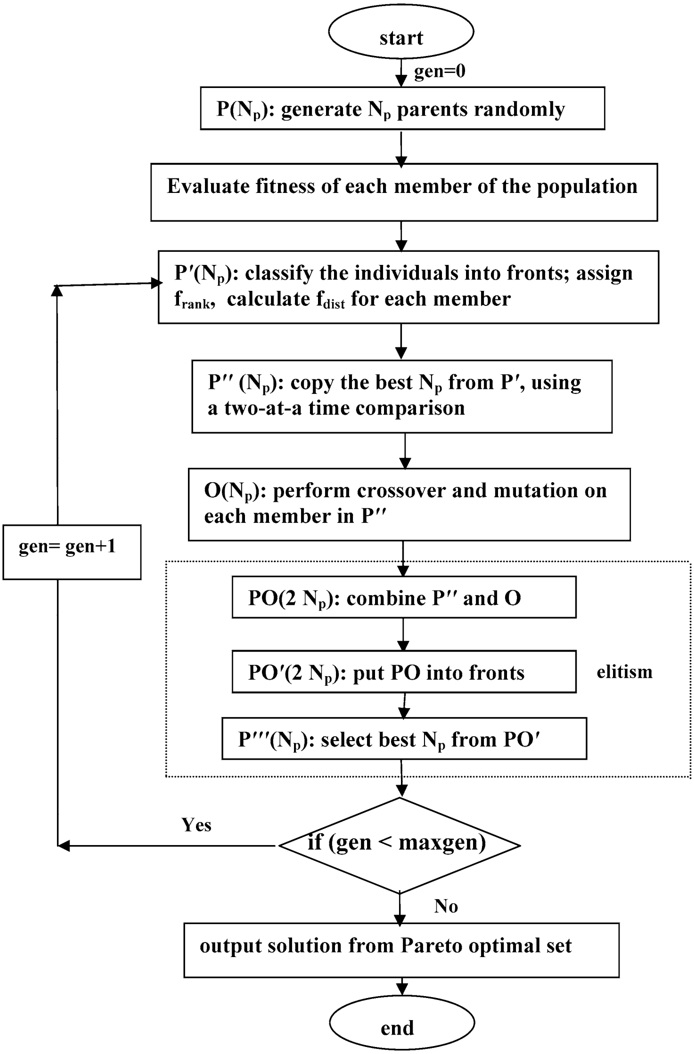


Figure 1. Flow chart of Multi-objective Genetic Algorithm.

3. Case Study

To evaluate the usefulness of the MOGA approach, Bhadra reservoir system is taken up as a case study for developing suitable operating policies. The Bhadra dam is located at latitude 13°42′ N and longitude 75°38′20″ E and is 1.5 km upstream of Lakkavalli village in Chikmagalur district of Karnataka state, India. Bhadra project is a multipurpose project providing for irrigation and hydropower generation, in addition to mandatory releases to the downstream to maintain water quality. The average annual rainfall in the catchment is 2,320 mm, with 90% of the rainfall occurring during monsoon period (June to November).

Table I. Salient features of Bhadra reservoir system

Characteristic	Quantity
Gross storage capacity	2,025 Mm^3
Live storage capacity	1,784 Mm^3
Dead storage capacity	241 Mm^3
Average Annual inflow	2,845 Mm^3
Left bank canal capacity	10 m^3/s
Right bank canal capacity	71 m^3/s
Left bank turbine capacity (PH1)	2,000 kW
Right bank turbine capacity (PH2)	13,200 kW
Riverbed turbine capacity (PH3)	24,000 kW

The reservoir provides water for irrigation of 6,367 ha and 87,512 ha under left and right bank irrigation canals respectively. Also under this project, there are three sets of hydropower turbines, one set each on the left bank canal and the right bank canal and the third at the bed level of the dam, for generating hydropower (WRDO, 1986 and Vedula and Mohan, 1990). Salient features of the reservoir are given in Table I. Figure 2 shows the schematic diagram of the Bhadra reservoir system.

The irrigated area, spread over the districts of Chitradurga, Shimoga, Chikmagalur, and Bellary in Karnataka state, comprises predominantly of red loamy soil, except in some portions of the right bank canal area, which consist of black cotton soil. Major crops grown in the command area are paddy, sugarcane, permanent garden, and semidry crops. Data of monthly inflows and other details were collected from Water Resources Development Organization (WRDO), Bangalore, covering a period of 69 years (from 1930–1931 to 1998–1999). The monthly crop water requirements were calculated using FAO Penman-Monteith method. In addition to

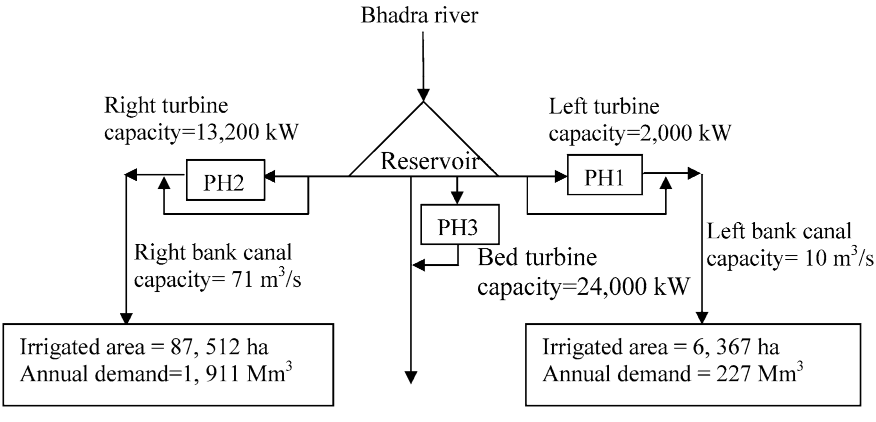


Figure 2. Schematic diagram of Bhadra reservoir system.

irrigation and hydropower, it is stipulated that a minimum release of 9 Mm^3 to downstream is to be made in each month to meet the downstream water quality requirements.

3.1. MATHEMATICAL MODEL FORMULATION

The objectives of the model are minimization of irrigation deficits and maximization of hydropower generation. These two are mutually conflicting objectives, since the one that tries for minimization of the irrigation deficits, requires more water to be released to satisfy irrigation demands and the other tries to maximize hydropower production, requiring higher level of storage in the reservoir to produce more power. These two competing objectives of the system are expressed as follows:

3.1.1. *Minimize Sum of Squared Deviations of Releases from Demands for Irrigation,*

$$\text{Minimize } SQDV = \sum_{t=1}^{12} (D_{1,t} - R_{1,t})^2 + \sum_{t=1}^{12} (D_{2,t} - R_{2,t})^2 \tag{2}$$

where *SQDV* is the sum of squared deviations of irrigation releases from demands. $D_{1,t}$ and $D_{2,t}$ are the irrigation demands for the left bank canal and right bank canal command areas respectively in period t in Mm^3; $R_{1,t}$ and $R_{2,t}$ are the releases into the left and right bank canals respectively in period t in Mm^3.

3.1.2. *Maximize Annual Energy Production*

$$\text{Maximize } E = \sum_{t=1}^{12} p(R_{1,t}H_{1,t} + R_{2,t}H_{2,t} + R_{3,t}H_{3,t}) \tag{3}$$

where E is the total energy produced in M kWh; p is power production coefficient; $R_{3,t}$ is the release to riverbed turbine in period t in Mm^3. $H_{1,t}$, $H_{2,t}$, $H_{3,t}$ are the net heads available to left bank, right bank and riverbed turbines respectively in meters during period t.

The optimization is subject to the following constraints:

3.1.3. *Storage Continuity*

$$S_{t+1} = S_t + I_t - (R_{1,t} + R_{2,t} + R_{3,t} + E_t + O_t) \quad \text{for all} \quad t = 1, 2, \ldots, 12 \tag{4}$$

where S_t = Active reservoir storage at the beginning of period t in Mm^3; I_t = inflow to the reservoir during period t in Mm^3; E_t = the evaporation losses during period t in Mm^3 (a non-linear function of initial and final storages of period t); O_t = overflow from the reservoir in period t in Mm^3;

3.1.4. *Storage Limits*

$$S_{\min} \leq S_t \leq S_{\max} \quad \text{for all } t = 1, 2, \ldots, 12 \tag{5}$$

where $S_{\min}$ and $S_{\max}$ are the minimum and maximum active storages of the reservoir.

3.1.5. *Maximum Power Production Limits*

$$pR_{1,t}\, H_{1,t} \leq E_{1,\max} \quad \text{for all } t = 1, 2, \ldots, 12 \tag{6}$$

$$pR_{r,t}\, H_{2,t} \leq E_{2,\max} \quad \text{for all } t = 1, 2, \ldots, 12 \tag{7}$$

$$pR_{3,t}\, H_{3,t} \leq E_{3,\max} \quad \text{for all } t = 1, 2, \ldots, 12 \tag{8}$$

where, $E_{1,\max}$, $E_{2,\max}$, and $E_{3,\max}$ are the maximum amounts of power in M kWh, that can be produced (turbine capacity) by the left, right and bed level turbines respectively.

3.1.6. *Canal Capacity Limits*

$$R_{1,\,t} \leq C_{1,\max} \qquad \text{for all } t = 1, 2, \ldots, 12 \tag{9}$$

$$R_{2,\,t} \leq C_{2,\max} \qquad \text{for all } t = 1, 2, \ldots, 12 \tag{10}$$

where, $C_{1,\max}$ and $C_{2,\max}$ are the maximum canal carrying capacities of the left and right bank canals respectively.

3.1.7. *Irrigation Demands*

$$D1_{\min,\,t} \leq R_{1,\,t} \leq D1_{\max,t} \qquad \text{for all } t = 1, 2, \ldots, 12 \tag{11}$$

$$D2_{\min,\,t} \leq R_{2,\,t} \leq D2_{\max,t} \qquad \text{for all } t = 1, 2, \ldots, 12 \tag{12}$$

where, $D1_{\min,\,t}$ and $D1_{\max,\,t}$ are minimum and maximum irrigation demands for left bank canal respectively; $D2_{\min,\,t}$ and $D2_{\max,\,t}$ are minimum and maximum irrigation demands for right bank canal respectively in time period t.

3.1.8. *Water Quality Requirements*

$$R_{3,\,t} \geq MDT_t \quad \text{for all } t = 1, 2, \ldots, 12 \tag{13}$$

where, MDT_t = minimum release to meet downstream water quality requirement in Mm^3.

It may be noticed that the above formulation involves non-linear optimization, due to the following reasons. In Equation (3) power generated is a non-linear function of release and head causing the flow. In Equation (4) evaporation loss is a function of non-linear relation between water spread area and average storage. The constraints on power production are also non-linear (Equations (6) to (8)).

4. Model Application

To apply MOGA to the above formulated model three inflow scenarios into the reservoir have been analyzed. These are:

Scenario 1: Mean monthly inflows – 0.5* SD
Scenario 2: Mean monthly inflows
Scenario 3: Mean monthly inflows + 0.5* SD
where SD = standard deviation of monthly inflows.

These three inflow scenarios can represent dry, normal and wet seasons in the region respectively. The parameters used in applying MOGA to reservoir operation model were selected after a thorough sentivity analysis by varying each of the parameters. A population size of 200 and a maximum generation number of 1000 are chosen to run the model. Since the problem involves real parameter variables, the model uses simulated binary crossover (SBX) and polynomial mutation operators (Deb, 2001). The parameters for genetic operators chosen are crossover probability (p_c) of 0.9 and a variable-wise mutation probability (p_m) of 0.03. The distribution index for SBX is 10 and that for mutation operator is 100. It can be noted that, the total number of decision variables of the model is 36, which is equal to the dimension of the problem. The model is run for the three inflows scenarios, under three priority conditions and the results are presented in the next section.

5. Results and Discussion

The MOGA approach is applied to Bhadra reservoir system to derive operating policies for the multipurpose reservoir system under multiple objectives. In general, for any multi-objective optimization problem, no single solution is said to optimal, and fortunately with MOGA approach, it is possible to generate different alternatives in a single run, and this helps in plotting the transformation curve between the objectives, which consequently helps the decision maker to make a suitable decision. Figure 3 shows a set of well-distributed solutions along the Pareto optimal front for the three different inflow scenarios, viz., dry, normal and wet seasons. In multi-objective optimization, after arriving at Pareto front, the remaining task is decision-making which requires a subjective judgment by the decision maker based on his preferences. The MOGA model generates a large number of alternatives. To choose the best solution among the many alternatives, a preliminary treatment of the solution is thus generally required, which in some cases may be computationally cumbersome. To facilitate easiness in decision making, a filtering is performed using a simple clustering technique for obtaining a representative subset of the non-dominated points. In Figures 3a, b and c, the points of shaded dots represent a total of 200 nondominated points that were generated, while the points of dark diamonds represent the 20 filtered nondominated solutions. When there is equal priority for irrigation and hydropower, it aims at concurrently maximizing

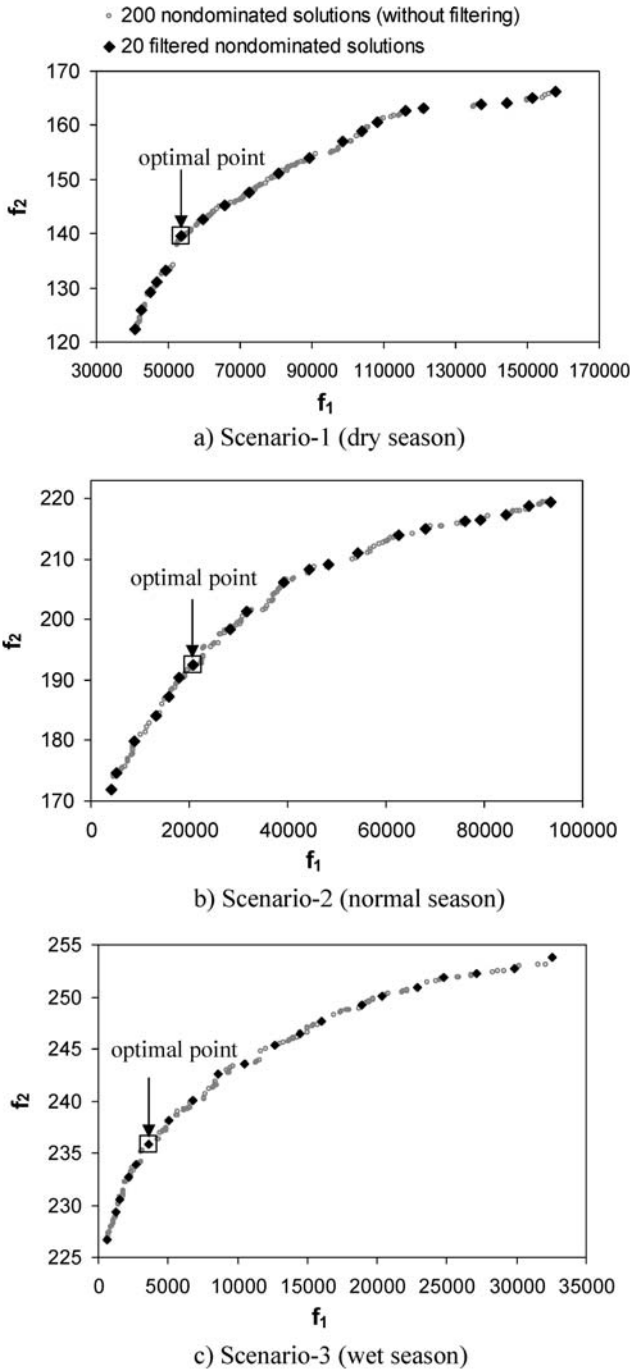


Figure 3. Pareto optimal front, showing the trade-off between irrigation (f_1) and hydropower (f_2) for different inflow scenarios. (f_1 = sum of squared irrigation deficits, $(\mathrm{Mm}^3)^2$; f_2 = hydropower generated, MkWh)

benefits from both the objectives. The points shown in square boxes represent the compromise solutions. For selection of these optimal points, the marginal rate of substitution approach (Deb, 2001) is used. The marginal rate of substitution is the amount of improvement in one objective function which is obtained by sacrificing unit decrement in any other objective function. The solution having the maximum marginal rate of substitution is the one chosen by this method. Thus the optimal point is the solution, which corresponds to maximum slope for the two-objective Pareto front. Therefore the optimal points are chosen in such a way that the compromised highest net benefits can be achieved with respect to both the objectives, i.e., irrigation (f_1) and hydropower (f_2). For inflow scenario 1 (Figure 3a), which represents the dry season, the optimal point is at $f_1 = 53,623.88$ $(\text{Mm}^3)^2$ and $f_2 = 139.472$ MkWh, where f_1 is the squared annual irrigation deficits, which is the sum of all the monthly squared deficits of irrigation over a year and f_2 is the total hydropower that can be generated in a year. For inflow scenario 2 (Figure 3b), which represents the normal season, the optimal point is at $f_1 = 20,714.62$ $(\text{Mm}^3)^2$ and $f_2 = 192.488$ MkWh and for inflow scenario 3 (Figure 3c), which represents the wet season, the optimal point is at $f_1 = 3,592.734$ $(\text{Mm}^3)^2$ and $f_2 = 235.848$ MkWh. The corresponding solutions for these three scenarios represent the storage and release policies for reservoir operation, when there is equal priority for irrigation and hydropower. To accommodate other alternative priorities, the model is also solved for two more sets of priorities; viz., only irrigation as the priority and only hydropower as the priority.

Figure 4 shows the storage operation policies for the three priorities, where 4a, b and c shows policies for the three inflow scenarios. Here it can be clearly observed that, if the reservoir is having hydropower as the only priority, it tends to keep the storage head in the reservoir at a high level to produce more power throughout the season, whereas for priority for irrigation this is reversed, which requires higher releases throughout the season to satisfy the irrigation demands. Thus these two conflicting situations can be clearly seen for all three scenarios.

The optimal release policies for left bank canal (R1), Right bank canal (R2) and for riverbed (R3) for the three priorities and for the three seasons are shown in Figures 5 to 7. Here it may be noticed that water releases made to left bank (R1) and right bank (R2) canals will generate hydropower, if the head is within the allowable limits of the turbines. If the head is lower it can only meet the irrigation demands, where as the releases to riverbed (R3) turbine will generate hydropower, and then meet the downstream water quality requirements in the river. If the reservoir operator opts for equal priority to maximize net benefits from irrigation and hydropower, then the optimal release policies obtained for the three inflow scenarios are shown in Figure 5a, b and c for dry, normal and wet seasons respectively. Figure 6 shows the release policies for the three inflow scenarios, when the reservoir operator gives priority only for irrigation. Here it can be observed that there is high reliability in meeting the irrigation demands, in all the three types of inflow scenarios as compared to earlier case and the releases to river bed are cut down drastically, limiting

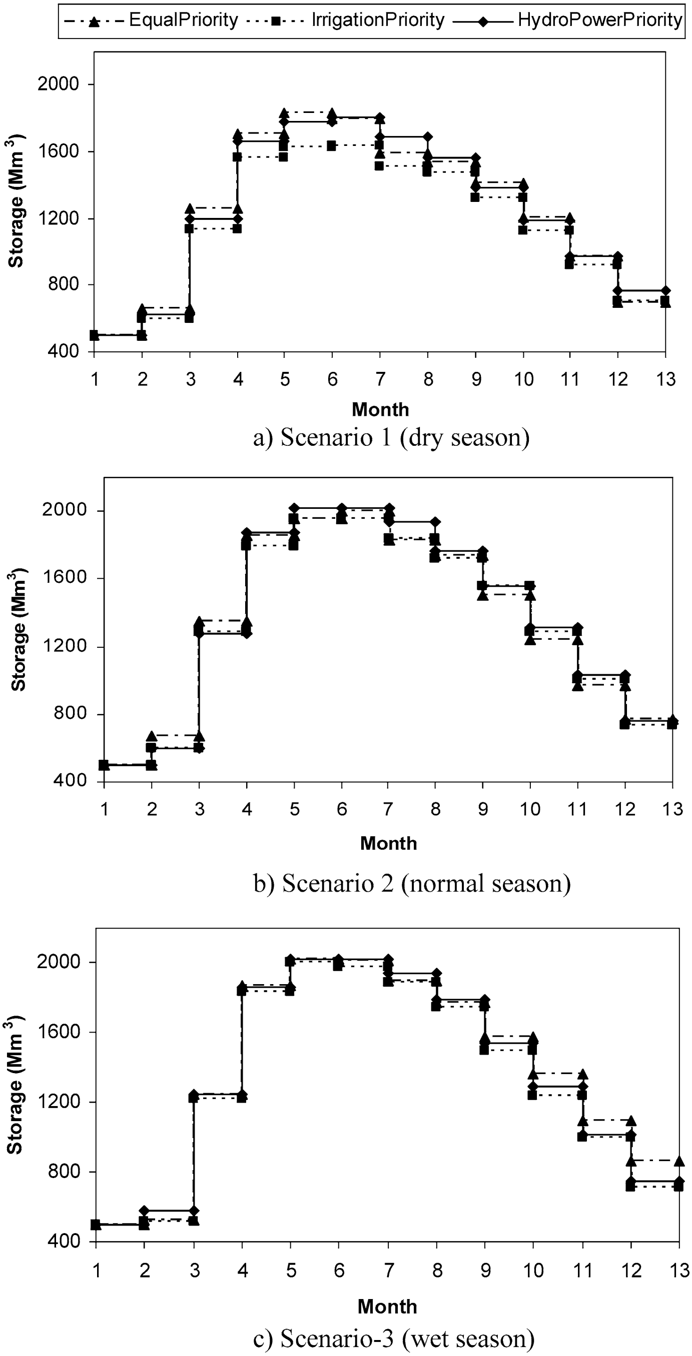
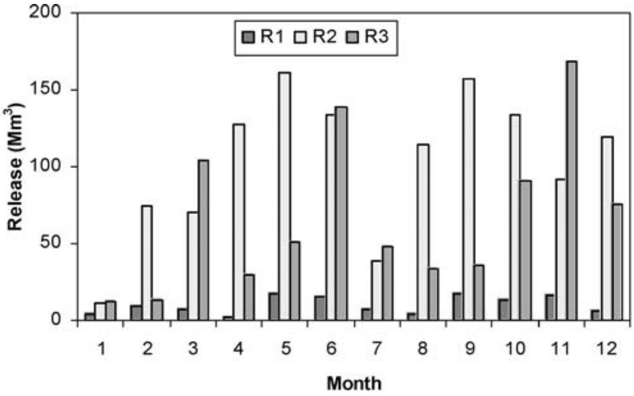
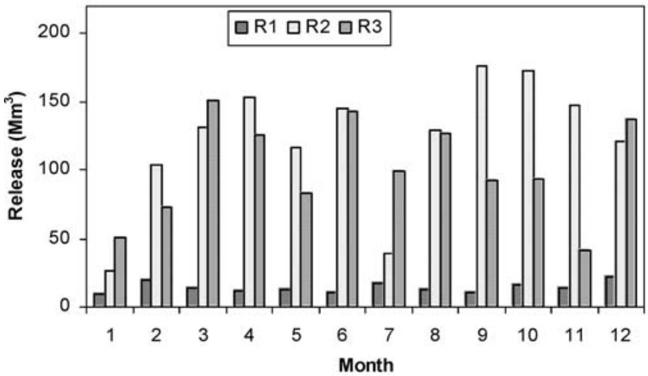


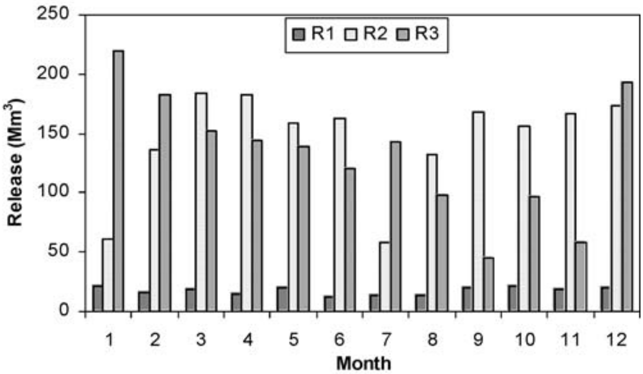
Figure 4. Reservoir storage policies for different inflow scenarios, showing the initial storages for different situations, viz., equal priority case, irrigation is the only priority case and hydropower is the only priority case.



a) Scenario 1 (dry season)

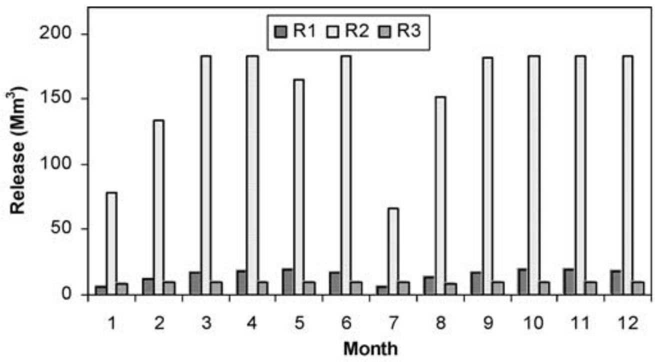


b) Scenario-2 (normal season)

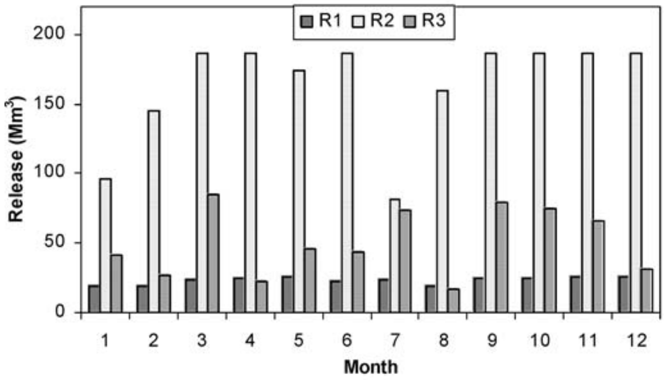


c) Scenario-3 (wet season)

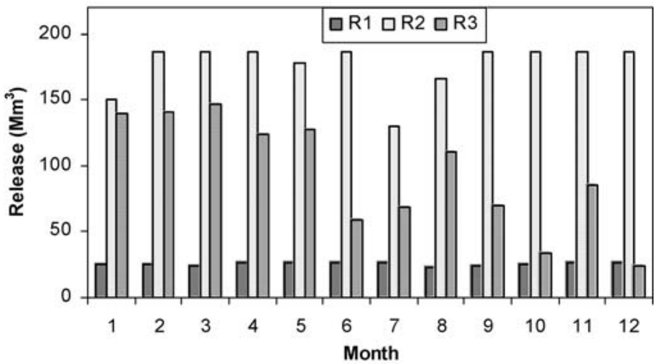
Figure 5. Optimal release policy obtained for equal priority case, showing releases in Mm^3 for left bank canal (R1), right bank canal (R2) and river bed (R3) for different inflow scenarios.



a) Scenario 1 (dry season)

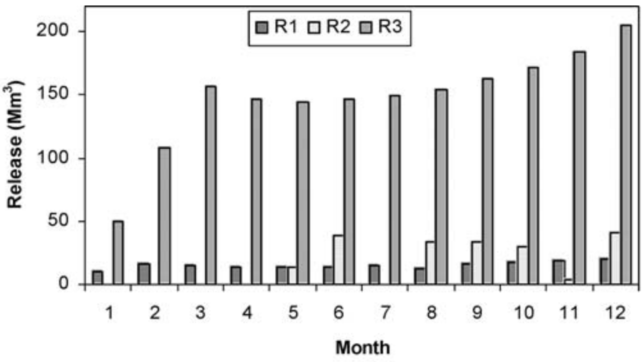


b) Scenario-2 (normal season)

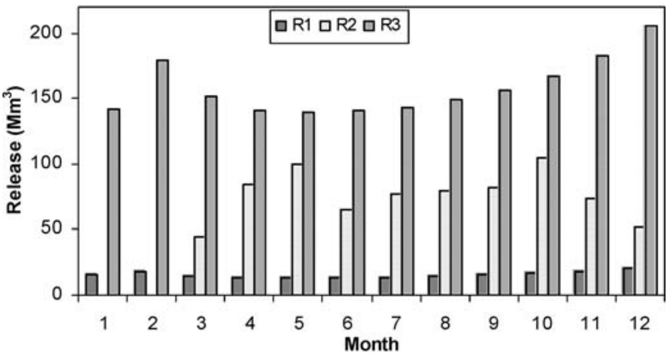


c) Scenario 3 (wet season)

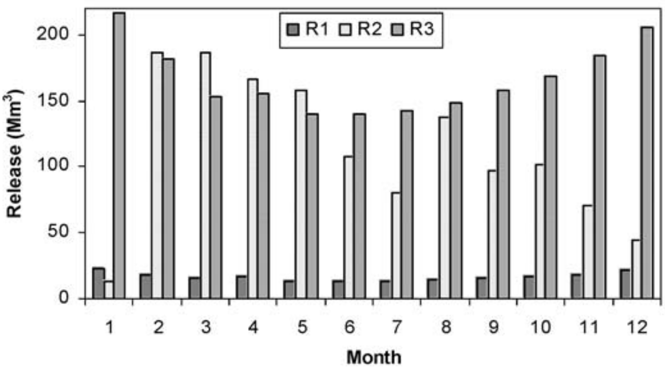
Figure 6. Optimal release policy obtained when only irrigation is given priority, showing releases in Mm^3 for left bank canal (R1), right bank canal (R2) and river bed (R3) for different inflow scenarios.



a) Scenario 1 (dry season)



b) Scenario-2 (normal season)



c) Scenario 3 (wet season)

Figure 7. Release policy obtained when only hydropower is priority, showing releases in Mm^3 for left bank canal (R1), right bank canal (R2) and river bed (R3) for different inflow scenarios.

to the minimum quantity to meet water quality requirements downstream. If the reservoir operator opts for hydropower as the only priority, then the optimal release policies obtained are shown in Figure 7a, b and c for the three inflow scenarios. It can be noticed that releases for irrigation purposes are reduced significantly in this case. The dominant release is the release to river bed turbine, where higher hydropower can be produced for the given release, compared to the left bank and right bank turbines, due to the availability of higher head.

The alternative storage and release policies can help the reservoir operator in making a suitable decision for different inflow scenarios and for different priorities accorded. The multi-objective GA approach is thus very much useful, in producing a well defined solution set for the conflicting objectives and eventually helps for better operation requiring short computational time.

6. Conclusion

In this study, a Multi-objective Genetic Algorithm (MOGA) approach has been applied for optimization of a multi-objective reservoir operation problem. In the MOGA method, a non-dominated sorting approach is used, which has a selection operator, elitism mechanism and the crowded distance operator to obtain efficient solutions. A multi-objective model is formulated with irrigation and hydropower as two competing objectives and the MOGA is applied to derive reservoir operation policies for Bhadra reservoir system, in India. The model is applied for three different inflow scenarios, and the corresponding Pareto optimal fronts are obtained for the three scenarios. Also in this study three kinds of priorities of the two objectives are analyzed and the respective operating policies are presented. The main advantage of the MOGA approach is finding many Pareto optimal solutions in a single run, which is attractive and efficient too and helps the decision maker to take suitable decisions at different levels. Thus this study has successfully demonstrated the efficacy and usefulness of MOEAs for evolving multi-objective reservoir operation policies.

References

Cieniawski, S. E., Eheart, J. W., and Ranjithan, S., 1995, 'Using genetic algorithms to solve a multi-objective groundwater monitoring problem', *Water Resour. Res.* **31**, 399–409.

Cohon, J. L. and Marks, D. H., 1973, 'Multi-objective screening models and water resources assessment', *Water Resour. Res.* **9**, 826–836.

Cohon, J. L. and Marks, D. H., 1975, 'A review and evaluation of multiobjective programming techniques', *Water Resour. Res.* **11**, 208–220.

Croley, T. E. II and Rao, K. N. R., 1979, 'Multi-objective risks in reservoir operation', *Water Resour. Res.* **15**, 1807–814.

Deb, K., 2001, 'Multi-Objective Optimization using Evolutionary Algorithms', John Wiley & Sons, Chichester, UK.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T., 2002, 'A fast and elitist multiobjective genetic algorithm: NSGA-II', *IEEE Trans. Evol. Comput.* **6**, 182–197.

Fonseca, C. M. and Fleming, P. J., 1995, 'An overview of evolutionary algorithms in multiobjective optimization', *Evol. Comput.* **3**, 1–16.

Goicoechea, A., Hansen, D. R., and Duckstein, L., 1982, 'Multi-objective decision analysis with engineering and business applications', John wiley & sons, New York.

Goldberg, D. E., 1989, *Genetic Algorithms in Search, Optimization and Machine Learning*, Reading, MA: Addison-Wesley.

Haimes, Y. Y., Tarvainen, K., Shima, T., and Thadathil, J., 1990, Hierarchical Multiobjective Analysis of Large-Scale Systems, Hemisphere Publishing co. Newyork.

Horn, J., Nafpliotis, N. and Goldberg, D. E., 1994, 'A niched pareto genetic algorithm for multiobjective optimization', in *Proc. 1st IEEE Conf. Evolutionary Computation, IEEE World Congr. Computational Computation*, Piscataway, NJ, **1**, pp.82–87.

Knowles, J. and Corne, D., 1999, 'The Pareto archived evolution strategy: A new baseline algorithm for multiobjective optimization', in *Proceedings of the 1999 Congress on Evolutionary Computation*, Piscataway, NJ: IEEE Press, pp.98–105.

Liang, Q., Johnson, L. E. and Yu, Y. S., 1996, 'A comparison of two methods for multiobjective optimization for reservoir operation', *Water Resources Bulletin* **32**, 333–340.

Loucks, D. P., Stedinger, J. R., and Haith, D. A., 1981, *Water Resource Systems Planning and Analysis*, Prentice-Hall, Englewood Cliffs, N.J.

Mohan, S. and Raipure, D. M., 1992, 'Multiobjective analysis of multireservoir system', *J. Water Resour. Plng. and Manage. ASCE* **118**, 356–370.

Oliveira, R. and Loucks, D. P., 1997, 'Operating rules for multireservoir systems', *Water Resour. Res.* **33**, 839–852.

Raj, P. A. and Kumar, D. N., 1996, 'Ranking of river basin alternatives using ELECTRE', *Hydrological Sciences Journal* **41**, 697–713.

Ritzel, B. J., Eheart, J. W., and Ranjithan, S., 1994, 'Using genetic algorithms to solve a multiple objective groundwater pollution containment problem', *Water Resour. Res.* **30**, 1589.

Sharif, M. and Wardlaw, R., 2000, 'Multireservoir system optimization using genetic algorithms: Case study', *J. Comp. in Civ. Engrg. ASCE* **14**, 255–263.

Srinivas, N. and Deb, K., 1994, 'Multiobjective optimization using nondominated sorting in genetic algorithms', *Evol. Comput.* **2**, 221–248.

Tauxe, G. H., Inman, R. R., and Mades, D. M., 1979, 'Multi-objective dynamic programming with application to reservoir', *Water Resour. Res.* **15**, 1403–1408.

Thampapillai, D. J. and Sinden, J. A., 1979, 'Tradeoffs for multiple objectives planning through linear programming', *Water Resour. Res.* **15**, 1028–1034.

Vedula, S. and Mohan, S., 1990, 'Real-time multipurpose reservoir operation: A case study', *Hydrological Sciences Journal* **35**, 447–462.

Wardlaw, R. and Sharif, M., 1999, 'Evaluation of genetic algorithms for optimal reservoir system operation', *J. Water Resour. Plng. and Manage. ASCE.* **125**, 25–33.

WRDO., 1986, 'Bhadra Reservoir Project', Project report, Water Resources Development Organization, Government of Karnataka, Bangalore, India.

Yeh, W.W.-G., 1985, 'Reservoir management and operations models: A state-of-the-art review', *Water Resour. Res.* **21**, 1797–1818.

Yeh, W.W-G. and Becker, L., 1982, 'Multiobjective analysis of multreservoir operations', *Water Resour. Res.* **18**, 1326–1336.

Zitzler, E., Deb, K. and Thiele, L., 2000, 'Comparison of multiobjective evolutionary algorithms: Empirical results', *Evol. Comput.* **8**, 173–195.

Zitzler, E. and Thiele, L., 1999, 'Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach,' *IEEE Trans. Evol. Comput.* **3**, 257–271.