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ORIGINAL PAPER

Evolving strategies for crop planning and operation of irrigation reservoir system using multi-objective differential evolution

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Abstract In this paper multi-objective differential evolution (MODE) approach is proposed for the simultaneous evolution of optimal cropping pattern and operation policies for a multi-crop irrigation reservoir system. In general, farming community wants to maximize total net benefits by irrigating high economic value crops over larger area, which may also include water-intensive crops and longer duration crops. This poses a serious problem under water-scarce conditions and often results in crop failure. Under varying hydrological conditions, the fixed cropping pattern with conventional operating rule curve policies may not yield economically good results. To provide flexible policies, a nonlinear multi-objective optimization model is formulated. To achieve robust performance by handling interdependent relationships among the decision variables of the model, the recent MODE technique is adopted to solve the multi-objective problem. The developed model is applied for ten-daily reservoir operation to a case study in India. The model results suggest that changes in the hydrologic conditions over a season have considerable impact on the cropping pattern and net benefits from the irrigation system. Towards this purpose, the proposed MODE model can be used to evolve different strategies for irrigation planning and reservoir operation policies, and to select the best possible solution appropriate to the forecasted hydrologic condition.

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Introduction

Uneven spatial and temporal distribution of precipitation in arid and semiarid climates of India causes frequent droughts in many parts of the country. The limited availability of water resources and continually increasing demands of water for various purposes pose a challenging task for water managers. This leads to the urgent need for rational use of the available water resources. Reservoir operation is the major component of water resource management. As agriculture is the predominant user of most of the water resources, efficient use of water for irrigation can help in sustainable development of the region.

A typical reservoir operation model for irrigation should integrate reservoir release decisions with crop water allocation decisions. Under a multi-crop environment, the various crops compete for the available water whenever the water available is less than the irrigation demands. In water-scarce conditions, the deficit allocation among the competing crops has significant influence on irrigation system performance. Given that water is the most important factor affecting crop yield, the knowledge of crop response to different deficit conditions helps in the selection of the most appropriate water management plan in irrigated agriculture. In addition to rational water use, there is a need for selecting economically viable cropping patterns for the command area. In general, the farming community prefers to maximize total net benefits by growing high economic value crops over larger area. It may also include water-intensive crops and longer-duration crops. This usually poses a serious problem under water-scarce conditions and often results in crop failure. Under varying hydrological conditions, the fixed cropping pattern with conventional operating rule curve policies may not yield economically good results. In arid and semi-arid situations, this approach often results in huge losses to the farmers. In this case, an adaptive cropping pattern and flexible operating policy may enhance the performance of the reservoir system.

For optimal allocation of irrigation water, models were developed based on stochastic dynamic programming (SDP) for single crop situation (e.g., Dudley et al. 1971; Dudley and Burt 1973; Bras and Cordova 1981) and for multi-crop situation (e.g., Rao et al. 1990; Vedula and Mujumdar 1992; Vedula and Nagesh Kumar 1996) to maximize the crop yields. Most of the studies considered maximization of relative yield as the objective function and are modeled for fixed cropping pattern. The objective function does not consider the effect of the extent of the area under a crop on the model performance as it causes biased influence in the water allocation for multiple crops. Also, the model does not consider the adaptive cropping pattern strategy for the variability in hydrologic conditions for the ensuing season. However, to overcome the abnormal climatic conditions (e.g., droughts) and to maximize the overall benefits from the irrigation system, an adaptive policy is essential to achieve the goals of efficient irrigation water management. This requires simultaneous evolution of optimal cropping pattern and operation policies for a reservoir system meant for irrigation of multiple crops.

In this study, the mutli-objective differential evolution-(MODE) based multi-objective methodology is proposed to evolve strategies for irrigation crop planning and operation policies for a reservoir system. The main objectives of the present study are: (1) to develop an efficient approach to account for variability in hydrologic conditions and formulate a multi-objective model for evaluating strategies for integrated irrigation planning and reservoir operation. (2) To solve the developed model using an efficient multi-objective differential evolution algorithm and evaluate the model performance for different hydrologic conditions.

In the following section, details of multi-objective reservoir operation model for multi-crop irrigation are described.

Multi-objective model for multi-crop irrigation system

In reservoir operation modeling for irrigation of multiple crops, under water-scarce conditions with fixed cropping pattern, no single objective function provides proper basis to avoid the influence of the extent of area on the crop water allocation decisions. This necessitates the development of a multi-objective model, where the crop area also need to be optimized simultaneously with crop water allocations, while aiming at maximum benefits from the irrigation system by utilizing available water resources.

The mathematical model basically consists of two components, one at reservoir level and another at farm level. The reservoir operation component optimally releases water from the reservoir, whereas multi-crop water allocation component allocates water to different crops, by properly encoding the sensitivity of crop yield to moisture stress during various physiological growth stages of the plants. The multi-objective model for reservoir operation has maximizing total crop area and maximizing total net benefits, as two competing objectives and is modeled as follows.

Objective function 1

By considering the relative yields and the resultant economic benefits, the objective function for maximizing the total net benefits from the irrigation system is expressed as:

$$f_1 = \sum_{c=1}^{NC} A_c \left[\mathrm{YB}_c \, \mathrm{RY}_c - \mathrm{PC}_c \right] \tag{1}$$

where NC is total number of crops grown in the irrigated area; YB_c and PC_c are yield benefit and production cost, respectively, for crop c (Rs/ha); RY_c is the relative yield of crop c, i.e., ratio of actual yield to potential yield $(Y_a/Y_p)_c$; A_c is irrigated area for crop c.

Based on Rao et al. (1990), the relative yield (RY) for each crop c is expressed as,

$$\mathrm{RY}_c = \prod_{t=T0_c}^{\mathrm{NTP}_c} \left[1 - ky_c^t \left(1 - \frac{\mathrm{AET}_c^t}{\mathrm{PET}_c^t} \right) \right] \tag{2}$$

where AET_c^t and PET_c^t are actual evapotranspiration (mm) and potential evapotranspiration (mm), respectively; $T0_c$ and NTP_c are starting and ending time periods, respectively, for the crop c; ky_c^t is yield stress sensitivity factor.

Objective function 2

Maximize the total irrigated area in the command area,

$$f_2 = \sum_{c=1}^{NC} A_c \tag{3}$$

The multiple objectives (Eqs. 1, 3) of the model are subjected to the crop area constraints, relative yield constraints and water availability constraints at reservoir level and at farm level, which are expressed as follows (Janga Reddy and Nagesh Kumar 2007a):

Crop area constraints

Since the farmers in the region predominantly depend on agricultural economy, it requires to ensure production of certain cash crops in addition to food crops. Therefore, the constraints of minimum and maximum area restrictions are expressed as,

$$A_c^{\min} \leq A_c \leq A_c^{\max} \quad \forall c \tag{4}$$

where $A_c^{\min}$ and $A_c^{\max}$ are minimum and maximum limits of the cropped area.

Relative yield constraint

The process of growing a crop necessarily involves production costs for seeds, fertilizers, labor, cultivation, etc., So the model is required to at least recover the production cost, by getting some minimum relative yield from the crops grown in the command area. So the constraint is expressed as,

$$\mathrm{RY}_c \geq \mathrm{RY}_c^{\min} \tag{5}$$

where $\mathrm{RY}_c^{\min}$ is minimum relative yield, which should be achieved from crop c.

Depending on the total water availability under the reservoir system, and based on soil types and crop water requirements, the project authorities can plan the maximum area that can be irrigated under different crops.

Water availability constraints

Water availability constraints include the restrictions imposed on reservoir level and farm level resources.

Reservoir level constraints

This component deals with the reservoir releases to be made in each period to meet the irrigation demands, subject to reservoir system dynamics.

Reservoir water balance

This is governed by the reservoir storage continuity equation,

$$S_{t+1} = S_t + Q_t - R_t - \mathrm{EVP}_t - OVF_t \quad \forall t \tag{6}$$

where S_t = reservoir storage at the beginning of period t in Mm^3; Q_t = inflow into the reservoir during period t in Mm^3; R_t = release from the reservoir in period t in Mm^3; EVP_t = evaporation losses during period t in Mm^3 (a nonlinear function of initial and final storages of period t); OVF_t = overflow from the reservoir in period t in Mm^3.

Storage bounds

The reservoir storage is restricted by,

$$S_{\min} \leq S_t \leq S_{\max} \quad \forall t \tag{7}$$

where $S_{\min}$ and $S_{\max}$ are the minimum and maximum storage limits of the reservoir in Mm^3.

Farm level constraints

This component deals with allocation of water, released from the reservoir, among different competing crops at farm level.

Water available for irrigation

The water released from the reservoir (R_t), undergoes conveyance, application and other losses. The water actually available for irrigation at the farm level Q_t, is therefore a fraction of R_t, given by,

$$Q_t = \eta R_t \quad \forall t \tag{8}$$

where η is the conveyance efficiency accounting for all losses from the reservoir head regulator to the farm level.

Allocation constraints

Total water available for irrigation (Q_t) in a period must be equal to the total water actually allocated to all crops in that period.

$$Q_t = \sum_{c=1}^{\mathrm{NC}} q_c^t A_c \quad \forall t \tag{9}$$

where q_c^t is water allocation for crop c in period t.

Soil moisture balance

The root-zone water content decreases with transpiration and soil evaporation, and it increases with rainfall, irrigation and deepening of the root zone as the crop grows.

The general mass balance equation for soil moisture is,

$$\begin{aligned}\mathrm{SM}_c^{t+1} D_c^{t+1} &= \mathrm{SM}_c^t D_c^t + \mathrm{RF}_t + q_c^t - \mathrm{AET}_c^t \\ &+ \mathrm{SM}_c^{\max}(D_c^{t+1} - D_c^t) - \mathrm{DP}_c^t - \mathrm{SR}_c^t \quad \forall c, t\end{aligned} \tag{10}$$

where SM_c^t = available soil moisture at root zone for crop c in period t (mm/cm); D_c^t = root depth of crop c in period t (cm); RF_t = rainfall in period t (mm); q_c^t = water allocation for crop c in period t (mm); $\mathrm{SM}_c^{\max}$ = maximum available soil moisture at field capacity for crop c (mm/cm); DP_c^t and SR_c^t= deep percolation and surface runoff respectively in period t (mm); and the available soil moisture in any time period t is restricted to the maximum capacity of the soil,

$$\mathrm{SM}_c^t \leq \mathrm{SM}_c^{\max} \quad \forall c, t \tag{11}$$

At the beginning of the season, the soil moisture in the entire root zone is assumed to be at its field capacity for all the crops, due to preseason rainfall and also as the crop root depth is very small. This assumption can however be relaxed to suit field situation.

In Eq. (10), the model variables are computed as follows (Janga Reddy and Nagesh Kumar 2007a).

Crop root depth

The depth of the active soil reservoir from which the crops can extract water depends on the effective depth of root penetration into the soil. This depth increases with the crop growth and attains a maximum value by the end of the flowering period for most of the crops. Root depth as a function of time after planting is obtained using the Borg and Grimes (1986) sinusoidal function,

$$D_c^t = D_c^{\max} \left(0.5 + 0.5 \sin\left[3.03\left(\frac{(t - T0_c) + 1}{NTP_c - T0_c + 1}\right) - 1.47\right]\right) \quad \forall c, t \tag{12}$$

where $D_c^{\max}$ = maximum possible depth of effective root zone for crop c (cm).

Actual evapotranspiration

Actual crop evapotranspiration depends on the evaporative demand of the atmosphere, the crop growth stage, and the available soil moisture in the root zone. Among the several methods available for determining the reference evapotranspiration, the FAO Penman–Monteith method (Allen et al. 1998) is found to be more appropriate and is adopted in this study, which is given by

$$\mathrm{ET}_0 = \frac{0.408\,\Delta\,(R_n - G) + \gamma\left(\frac{900}{T+273}\right) u_2 (e_s - e_a)}{\Delta + \gamma\,(1 + 0.34\,u_2)} \tag{13}$$

where ET_0 = reference evapotranspiration (mm/day); R_n = net radiation (MJ/m^2 day); G = soil heat flux (MJ/m^2 day); Δ = slope of vapor pressure curve (kPa/°C); γ = psychometric constant (kPa/°C); u_2 = wind speed measured at 2 m height (m/s); T = air temperature at 2 m height (°C); e_s = saturation vapor pressure (kPa); e_a = actual vapor pressure (kPa).

The potential evapotranspiration is given by

$$\mathrm{PET} = K_c \mathrm{ET}_0 \tag{14}$$

where K_c = crop coefficient.

The actual evapotranspiration in relation to its potential rate is determined by considering whether the available water in the root zone is adequate or whether the crop will suffer from stress induced by water deficit. The actual evapotranspiration in each period is computed as follows:

$$\mathrm{AET}_c^t = \begin{cases} 0, & \mathrm{SM1}_c^t \leq \mathrm{WP} \\ \frac{\mathrm{PET}_c^t(\mathrm{SM1}_c^t - \mathrm{WP})}{(1-p)(\mathrm{FC} - \mathrm{WP})}, & \mathrm{WP} < \mathrm{SM1}_c^t \leq [\mathrm{WP} + (1-p)(\mathrm{FC} - \mathrm{WP})] \; \forall c, t \\ \mathrm{PET}_c^t, & \mathrm{SM1}_c^t \geq [\mathrm{WP} + (1-p)(\mathrm{FC} - \mathrm{WP})] \end{cases} \tag{15}$$

where WP = wilting point (mm/cm); FC = field capacity (mm/cm); p = crop water depletion factor and $\mathrm{SM1}_c^t = (\mathrm{SM}_c^t D_c^t + \mathrm{RF}_t + q_c^t)/D_c^t$.

Surface runoff

In the soil water balance equation, any excess water beyond the retention capacity of the soil drains out as surface runoff from the irrigated area.

$$\mathrm{SR}_c^t = \begin{cases} 0, & \mathrm{SM2}_c^t \le SM_c^{\mathrm{sat}} \\ (\mathrm{SM2}_c^t - \mathrm{SM}_c^{\mathrm{sat}})D_c^t, & \mathrm{SM2}_c^t > \mathrm{SM}_c^{\mathrm{sat}} \end{cases} \quad \forall c,t \tag{16}$$

where $\mathrm{SM}_c^{\mathrm{sat}}$ = saturated soil moisture content (mm/cm); and

$$\mathrm{SM2}_c^t = \left(\mathrm{SM}_c^t D_c^t + \mathrm{RF}_t + q_c^t - \mathrm{AET}_c^t + \mathrm{SM}_c^{\max}(D_c^{t+1} - D_c^t)\right)/D_c^t.$$

Deep percolation

When irrigation is applied, any excess beyond the field capacity will drain down as deep percolation, which is also included in soil moisture balance equation. An empirical equation is used for calculating the deep percolation component (Rao et al. 1990; Paul et al. 2000), which is given by,

$$DP_c^t = \begin{cases} 0, & \mathrm{SM3}_c^t \le FC \\ \left(\dfrac{v(\mathrm{SM}_c^{\mathrm{sat}})(\exp[\mathrm{SM3}_c^t - \mathrm{FC}] - 1)}{(\exp[\mathrm{SM}_c^{\mathrm{sat}} - \mathrm{FC}] - 1)}\right) D_c^t & \mathrm{FC} < \mathrm{SM3}_c^t \le \mathrm{SM}_c^{\mathrm{sat}} \end{cases} \forall c,t \tag{17}$$

where v = pore connectivity index; and

$$\mathrm{SM3}_c^t = \left(\mathrm{SM}_c^t D_c^t + \mathrm{RF}_t + q_c^t - \mathrm{AET}_c^t + \mathrm{SM}_c^{\max}(D_c^{t+1} - D_c^t) - \mathrm{SR}_c^t\right)/D_c^t.$$

The final multi-objective model formulation involves maximization of both the objective functions given in Eqs. (1) and (3) subject to constraints given in Eqs. (4–11).

Multi-objective evolutionary optimization

Evolutionary algorithms in irrigation water management

In recent past few applications of evolutionary computation techniques in single objective optimization for reservoir operation modeling (for example, Oliveira and Loucks 1997; Wardlaw and Sharif 1999; Cai et al. 2001; Nagesh Kumar et al. 2006) and for irrigation planning (for example, Kuo and Liu 2003; Raju and Nagesh Kumar 2004; Alvarez et al. 2004) were reported. For multi-objective optimization also researchers reported that multi-objective evolutionary algorithm (MOEA) can be a very useful tool for deriving reservoir operational policies. Janga Reddy and Nagesh Kumar (2006) applied a multi-objective genetic algorithm (MOGA) for evolving multi-objective reservoir operation policies for monthly operation of a reservoir system. They reported that MOGA procedure provides a wide range of alternative policies in a single run and gives flexibility to decision making for the reservoir operator. More recently Janga Reddy and Nagesh Kumar (2007b) proposed an efficient multi-objective optimization algorithm namely MODE technique, by incorporating non-dominated sorting and Pareto-optimality principles into single objective differential evolution algorithm. The efficiency of the developed MODE was evaluated for several test problems and it was found that the MODE technique was giving superior performance to that of non-dominated sorting genetic algorithm-II (NSGA-II). It is also noticed that the evolutionary operators used in DE algorithms are very much suitable for problems having interdependent relationships among the decision variables such as, in reservoir operation problems. Therefore it is proposed to use the MODE technique to solve the model developed in this study.

In the following, a brief description of differential evolution algorithm is presented first, and then step-by-step procedure of MODE methodology is explained.

Differential evolution

Differential evolution is a recent optimization technique in the family of evolutionary computation. It was proposed as a variant of evolutionary algorithms to achieve the goals of robustness in optimization and faster convergence to a given problem (Storn and Price 1995). Differential Evolution differs from other evolutionary algorithms in the mutation and recombination phase. Unlike some meta-heuristic techniques such as genetic algorithms and evolutionary strategies, where perturbation occurs in accordance with a random quantity, DE uses weighted differences between solution vectors to perturb the population. DE algorithm has very good exploration and exploitation capabilities through its evolutionary operators and has been proved to be significantly faster and robust for numerical optimization (Storn and Price 1997). Also DE is capable of optimizing all integers, discrete and continuous variables, and can handle nonlinear objective functions with multiple nontrivial solutions (Onwubolu and Davendra 2006).

In recent studies, it is reported that DE/rand-to-best/1/bin variant of differential evolution performs superior to its other variants (Janga Reddy and Nagesh Kumar 2007b) and so this variant of differential evolution algorithm is adopted in this study. In this variant, the perturbation is made with the vector difference of best vector of the previous generation (*best*) and current solution vector, plus single vector differences of two randomly chosen vectors (*rand*) among the population. The DE variant uses binomial (*bin*) variant of crossover operator, where the crossover is performed on each of the decision variables whenever a randomly picked number between 0 and 1 is within the crossover constant (CR) value. A brief description of the DE algorithm for the optimization problems with minimization type objective function is presented below.

DE algorithm

Let $S \subset R^n$ be the search space of the problem under consideration. Then, the differential evolution (DE) algorithm utilizes NP (population size), n-dimensional vectors,

$$X_i = (x_{i1}, \ldots, x_{in})^{\mathrm{T}} \in S, \quad i = 1, \ldots, \mathrm{NP},$$

as a population for each iteration, called a generation, of the algorithm. The initial population is usually taken to be uniformly distributed in the search space. At each generation, two operators, namely mutation and crossover, are applied on each individual, thus producing a new population. Then, a selection phase takes place, where each individual of the new population is compared to the corresponding individual of the old population, and the better between them is selected as a member in the population of the next generation (Storn and Price 1995).

According to the *mutation* operator, for each individual, $X_i^{(G)}$, $i = 1,\ldots,\mathrm{NP}$, at generation G, a mutation vector,

$$V_i^{(G+1)} = \left(v_{i1}^{(G+1)}, v_{i2}^{(G+1)}, \ldots, v_{in}^{(G+1)}\right)^{\mathrm{T}},$$

is determined using the Equation

$$V_i^{(G+1)} = X_i^{(G)} + F\left(X_{best}^{(G)} - X_i^{(G)}\right) + F\left(X_{r1}^{(G)} - X_{r2}^{(G)}\right) \tag{18}$$

where, $X_{\mathrm{best}}^{(G)}$ is the best individual of the population at generation G; $F > 0$ is a real parameter, called mutation constant, which controls the amplification of the difference between two individuals so as to avoid search stagnation; and r_1, r_2 are mutually different integers, randomly selected from the set $\{1,2,\ldots, i-1, i+1,\ldots, \mathrm{NP}\}$.

Following the mutation phase, the *crossover* operator is applied on the population. For each mutant vector, $V_i^{(G+1)}$, an index $rnbr(i) \in \{1,2,\ldots,n\}$ is randomly chosen, and a trial vector,

$$U_i^{(G+1)} = \left(u_{i1}^{(G+1)}, u_{i2}^{(G+1)}, \ldots, u_{in}^{(G+1)}\right)^{\mathrm{T}}$$

is generated, with

$$u_{ij}^{(G+1)} = \begin{cases} v_{ij}^{G+1}, & \text{if } (randb(j) \leq CR)\, or (j = rnbr(i)) \\ x_{ij}^{G}, & \text{if } (randb(j) > CR) \text{ and } (j \neq rnbr(i)) \end{cases} \tag{19}$$

where, $j = 1,2,\ldots,n$; $randb(j)$ is the j-th evaluation of a uniform random number generator within [0,1]; and CR is a user defined crossover constant in the range [0,1] (Storn and Price 1997). In other words, the trial vector consists of some of the components of a randomly selected individual of the population (i.e., the individual with index, $rnbr(i)$).

To decide whether the vector $U_i^{(G+1)}$ should be a member of the population of the next generation, it is compared with the corresponding vector $X_i^{(G)}$. Thus, if f denotes the objective function under consideration, then,

$$X_{ij}^{(G+1)} = \begin{cases} U_i^{G+1}, & \text{if } f(U_i^{G+1}) < f(X_i^G) \\ X_i^G, & \text{otherwise} \end{cases} \tag{20}$$

Thus each individual of the trial vector is compared with its parent vector and the better one is passed to the next generation, so the elitism (the best individuals in the population) is preserved. These steps are repeated until specified termination criterion is reached. DE's ability to provide efficient solutions for complex single objective optimization problems prompted to develop MODE algorithms (Janga Reddy and Nagesh Kumar 2007b), the details of which are given in the following section.

MODE

A multi-objective optimization problem involves a number of objective functions which are to be simultaneously optimized. Since an evolutionary algorithm (EA) deals with a number of population members in each generation, an EA is an ideal candidate for finding multiple Pareto-optimal solutions for a multi-objective optimization problem. In general, MOEA method is required to perform the following tasks: (1) emphasize non-dominated solutions for progressing towards the true Pareto-optimal front, (2) emphasize less-crowded solutions for maintaining a good diversity among the obtained solutions and (3) emphasize elites to provide a faster and reliable convergence towards the true Pareto-optimal front.

By combining Pareto-optimality (non-domination) criteria with DE algorithm, the MODE procedure was evolved. To achieve multi-objective goals, an effective selection procedure is adopted, where it uses non-dominated sorting and crowding distance assignment operators (Deb et al. 2002). This methodology also maintains an external archive to store the best non-dominated solutions explored over the generations. Brief details of MODE procedure are presented in the next subsection.

MODE procedure

The MODE algorithm consists of initialization of population, evaluation, Pareto-dominance selection, performing DE operations and reiterating the search on population to reach true Pareto optimal solutions. In this process, each of the members is first evaluated and checked for dominance relation. If the new member dominates the parent, then it replaces the parent. If the parent dominates the candidate, the new member is discarded. If the parent and new member both are mutually nondominant, then the two are added to a temporary population (*tempPop*). This step is repeated for all members of the population. Thereafter, in order to select the population for next generation, the *tempPop* is reduced to the population size (NP) by using non-dominated sorting and crowding distance assignment procedures. Apart from that, it uses *non-dominated elitist archive* (NEA) to store the best solutions found so far over the generations. These operators help to create effective selection pressure toward true Pareto optimal solutions. The size of NEA can be set to any desirable number of non-dominated solutions and in this study it is set to the Population size, NP. In case, the size of NEA exceeds NP, then the crowding operator is used to select the sparse individuals to achieve good distribution of Pareto optimal solutions. The selection of *best* is made by randomly choosing a solution from the elite archive, *NEA*.

The MODE procedure can be summarized in the following steps.

Step 1. Input the required DE parameters. Initialize all members of the vector population randomly in the limits of specified decision variables.
Step 2. Evaluate each member of the population. Identify individuals that give non-dominated solutions in the current population and store them in NEA. Set generation counter $G = 0$.
Step 3. Perform mutation and crossover operations on all the members of the population, i.e., for each Parent P_i

(a) Select distinct vectors randomly from the current population (primary vector) other than the parent vector. (i.e., randomly select $r_1, \ r_2 \ \in \{1,2,....,n\}$, such that $r_1 \neq r_2 \neq i$).
(b) Calculate new mutation vector using Eq. (18).
(c) Modify the mutated vector by binary crossover with the parent, using crossover probability CR (Eq. 19).
(d) Restrict the variables to the boundaries, if any variable is outside the lower or upper bound.

Step 4. Evaluate each member of the population. Check for dominance with its parents. If the new member dominates the parent, then it replaces the parent. If the parent dominates the new member, then it is discarded. If both are non-dominated to each other, then new member is added to a temporary population (*tempPop*).
Step 5. Add the latest solution vectors (current population) to the *tempPop*. Then use the non-dominated sorting and crowding assignment operators to select the individuals for next generation. Store the non-dominated solutions in NEA. If NEA size exceeds the desired number of Pareto optimal set, then select the desired number of the least crowded members with the help of crowding assignment operator. Empty the *tempPop*.
Step 6. Increase the generation counter, G to $G + 1$ and check for termination criteria. If the termination criterion is not satisfied, then go to step 3; otherwise output the non-dominated solution set from NEA.

Further details of the MODE procedure can be found in Janga Reddy and Nagesh Kumar (2007b), where MODE performance was evaluated for various standard test problems. The MODE is adopted in this study to solve the multi-objective optimization model developed for simultaneous irrigation crop planning and reservoir system operation.

Case study

The applicability of the model presented in the previous sections is demonstrated through a case study of an existing reservoir, namely Malaprabha reservoir system in the

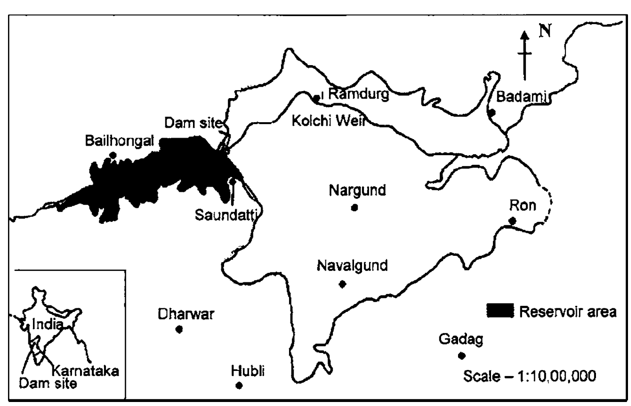

Fig. 1 Location map of Malaprbaha reservoir system

Krishna River Basin in Karnataka state, India. The Malaprabha dam is located in Belgaum district, Karnataka state, at latitude of 15° 49′ N and longitude of 75° 6′ E. The location map of Malaprabha reservoir project is shown in Fig. 1. The reservoir with a catchment area of 2,564 km^2 has a gross storage capacity of 1,070 Mm^3 and a live storage capacity of 830 Mm^3 ; and 75% dependable annual yield for the reservoir is 1,205 Mm^3. The mean annual rainfall in the command area is 576 mm. The reservoir mainly serves for irrigation purpose and is in operation since 1973. There are two major canals under this reservoir, providing irrigation to Dharwad, Belgaum, and Bijapur districts of Karnataka state. Black cotton soil is found predominantly in the major portion of the command area (71%) and red soil in the remaining area, under the right and left-bank canals. The major crops grown are cotton, wheat, sorghum, maize, safflower and pulses.

The data pertaining to the reservoir on inflows, withdrawals, pan evaporation, and area–capacity relationships were collected from Karnataka state Water Resources Development Organization (WRDO), Bangalore. Inflow data for a period of 53 years (from June 1951 to May 2004) and rainfall data for a period of 88 years (from June 1901 to May 1989) were available.

Model application

The decision interval for irrigation scheduling generally varies from weekly to fortnightly, depending on type of crop, properties of soil, geographical and climate characteristics of the region etc. For the present study, the time interval during which irrigation decision need to be taken is considered as 10 days. The water year begins on June 1 and ends by May 31 of next calendar year. Each month is divided into three periods; the first two 10-day periods having 10 days each, and the remaining days of the month as the third period. Thus a time interval of 10-days is adopted for reservoir operation and irrigation–allocation decisions. The growth stages of the crops were adjusted to be multiples of the decision intervals (10-day) and are modeled accordingly.

In a year, there are two principal cropping seasons: kharif (monsoon season: June–October, periods: 1–15) and rabi (non-monsoon season: November–March, periods: 16–30). Under this reservoir irrigation, a total of nine major crops, four in kharif, four in rabi and one two-seasonal crop, are considered. Table 1 gives the comprehensive details of principal crops grown in Malaprabha reservoir command, crop growth periods, planned irrigated area, etc., during a water year. The crop growth stages and yield response factors are adopted from Doorenbos and Kassam (1979). On an average, the crops require a total of 938.22 Mm^3 and 1,042.26 Mm^3 of water during kharif and rabi seasons, respectively. However, the crops grown in kharif season require only a small amount of the reservoir water, since for most of the time the crops were benefited by monsoon seasonal rainfall to meet their water requirements. But in rabi season, the rainfall is scarce and so the crops mostly depend on the reservoir water.

For model application, the inputs to the model include the initial storage of the reservoir at the starting of the period, inflows into the reservoir, rainfall in the command area, the potential evapotranspiration values for the crops and crop yield response factors for each growth stage. The soil moisture values at the beginning of crop growth were assumed to be at the field capacity of the soil for all the crops. The field capacity (FC) and wilting point (WP) are adopted as 3.5 and 1.7 mm/cm for black cotton soil, and 2.0 and 1.0 mm/cm for red soil, respectively; the crop water depletion factors (p) are taken as 0.4 and 0.5, for black cotton and red soils, respectively, and irrigation efficiency is taken as 50%.

The developed model is evaluated for four different hydrologic scenarios:

Scenario-1: Far below average hydrologic conditions: 0.6* INF_{avg}, and 0.6*$RAIN_{avg}$

Scenario-2: Below average hydrologic conditions: 0.8* INF_{avg}, and 0.8*$RAIN_{vg}$

Scenario-3: Average hydrologic conditions: 1.0* INF_{avg}, and 1.0*$RAIN_{avg}$

Scenario-4: Above average hydrologic conditions: 1.2* INF_{avg}, and 1.2*$RAIN_{avg}$

Table 1 Details of the crop area, crop growth periods, total crop water requirements (CWR) and economic data used in the model for kharif, rabi and two-seasonal crops (*US $1 = Rs. 46)

Season/ Crop	Max. area (ha)	Crop growth periods	Total CWR (Mm^3)	Crop yield (kg/ha)	Price (*Rs/100 Kg)
Kharif season					
Maize	40,094	1–13	323.725	1,820	540
Pulses	19,492	1–11	56.796	600	1,435
Sorghum	91,589	1–12	307.189	803	525
Ground nut	13,565	1–13	47.391	970	1520
Rabi Season					
Sorghum	40,144	15–27	171.972	803	525
Pulses	19,412	15–26	72.609	600	1,435
Wheat	80,470	15–28	363.966	2,692	650
Safflower	20,042	15–30	111.363	596	1,760
Two-seasonal					
Cotton	79,332	6–25	525.469	500	1,760

where INF_{avg} is average ten-daily inflows into the reservoir and $RAIN_{avg}$ is average ten-daily rainfalls in the command area.

Average values of inflows from 53 years' data and rainfall from 88 years' data are computed for each of the 36 time periods (ten-daily). It is assumed that the first three scenarios can provide a sufficient representation of the model under water-deficit conditions. It may be noted that the model can handle as well any other combination of water deficit conditions.

Results and discussion

The MODE technique is applied to the multi-objective model described in the previous section to arrive at suitable cropping pattern and reservoir operation policies for the four different hydrologic conditions. To run the MODE algorithm, the parameters chosen were: population size = 200; crossover probability (CR) = 0.3; mutation constant (F) = 0.5; and maximum number of generations = 1,500.

Generally for any multi-objective optimization problem, there will be no single solution which can be said to be optimal. But there exist a number of multiple noninferior or Pareto optimal solutions. Therefore, an ideal multi-objective optimization procedure basically will have two steps: (1) finding multiple tradeoff optimal solutions with a wide range of values for objectives and (2) choosing one of the obtained solutions using higher-level information.

The optimization has been carried out over 1-year time horizon for each of the hydrologic scenarios considered. The population-based MODE approach generates a wide variety of alternatives in the form of Pareto optimal solutions in a single run. This can help the decision maker in plotting the transformation curve between the objectives and to arrive at a suitable policy for implementation. For each alternative solution, the model gives detailed results. These include decisions both at reservoir level and at farm level. The decisions at reservoir level include reservoir releases, storages, evaporation losses and overflows for each time period of the two crop seasons. At farm level they include; the area of each crop, the irrigation water to be allocated, soil moisture status, actual evapotranspiration for each crop and for each period of the two seasons. It should be noted that the total area obtained in the solutions can be more than that of the total cultural command area, since some of the crops were grown in the same area in both the kharif and rabi seasons.

The operating policy corresponding to each noninferior solution is called a satisfactory operating policy and it can be discriminated from the optimal operating policy of the single-objective optimization. There are many ways to select the final compromising solution. However, this may require the decision maker's analysis and interpretation. In this study for final decision making, compromise programming approach (Deb 2001) is adopted. The method of compromise programming picks a solution which is minimally located from a given reference point. From the generated solutions, distance metric $d(f, z)$ and a reference point z have to be fixed for this purpose. Then the Tchebycheff metric is computed by,

Tchebycheff metric:

$$d(f,z) = \max_{m=1}^{M} \frac{(|f_m(x) - z_m|)}{\max\limits_{x \varepsilon S} (f_m(x) - z_m)} \tag{21}$$

where S is the entire search space; z_m is reference solution for objective function m. The reference point comprises of the individual best objective function values $z = (f_1^*, f_2^*, ..., f_M^*)^T$. Since this solution is nonexistent, the decision maker is interested in choosing a feasible solution, which is closest to this reference solution. So, the solution which has smaller metric value is the desired one.

Results obtained from the model for different hydrologic scenarios are discussed in the following sub-sections.

Scenario-1

For the far below average hydrologic conditions (scenario-1), the MODE model provides a wide set of well-distributed Pareto optimal solutions, as shown in Fig. 2a. It can be seen that the Pareto optimal front is showing a nonlinear relationship between the total irrigated area and total net benefits from the irrigation system. It also indicates that irrigating more area results in lesser total net benefits and vice-versa. For minimum guaranteed value of total net benefits, major contribution comes from the crops grown in kharif season. This is mainly due to the difference in crop water availability between the crops grown in the two seasons, since the kharif season crops receive plenty of rainfall and reservoir water would also be available during this season, but the rabi crops mainly depend on water supplied from the reservoir.

The Pareto front (Fig. 2a) provides a widespread of alternative solutions which range from 276.36×10^3 ha, Rs 1266.34 Million to 314.71×10^3 ha, Rs 808.24 Million)]. Here, any solution point in the objective space indicates irrigated area (in thousand ha) and total net benefits (in Million rupees). To facilitate decision making, a filtering is performed by selecting a representative subset of the nondominated points. For this a simple clustering technique is used (Deb 2001). In Fig. 2 the points of shaded dots represent a total of 200 nondominated points that were

Fig. 2 Results of the multi-objective model for the different hydrologic conditions, showing the trade-off curve between irrigated area and total net benefits. The *square box* indicates the preferred alternative

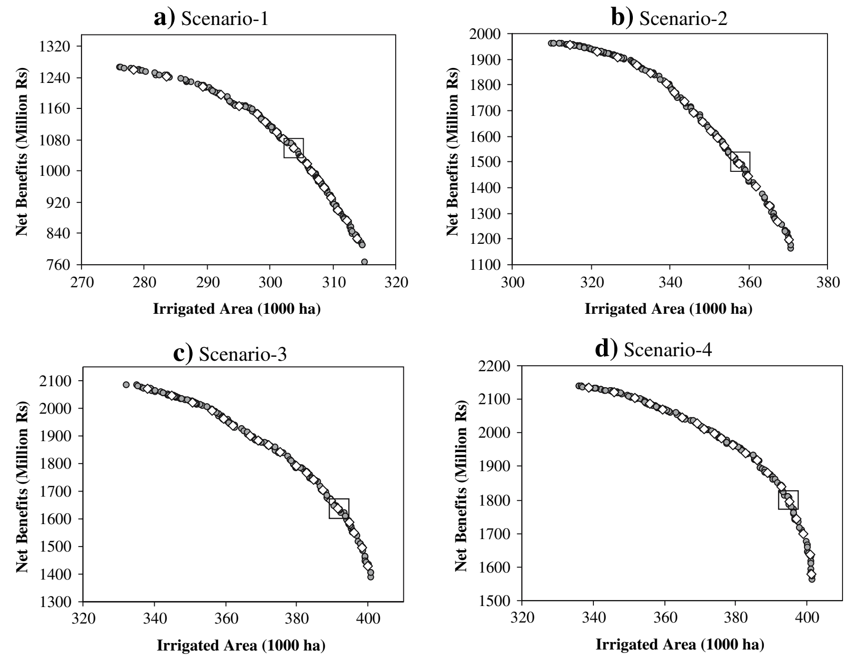

Table 2 Results of the selected best compromised Pareto optimal solution for the four hydrologic scenarios, giving details of crop area, A_c (ha), relative yield, RY_c and net benefit, NB_c (Million Rs) for kharif, rabi and two-seasonal crops

Season/Crop	Scenario-1			Scenario- 2			Scenario-3			Scenario-4		
	A_c	RY_c	NB_c	A_c	RY_c	NB_c	A_c	RY_c	NB_c	A_c	RY_c	NB_c
Kharif												
Maize	40,085.29	0.5006	65.91	40,077.24	0.9981	261.84	40,094.00	1.0000	262.70	40,068.26	1.0000	262.53
Pulses	19,440.47	1.0000	111.59	19,417.56	1.0000	111.46	19,418.40	1.0000	111.46	19,492.00	1.0000	111.88
Sorghum	91,589.00	0.8483	198.85	91,535.40	1.0000	257.26	91,581.95	1.0000	257.39	91,589.00	1.0000	257.41
Ground nut	13,554.27	1.0000	133.23	13,461.32	1.0000	132.32	13,563.07	1.0000	133.32	13,518.96	1.0000	132.88
Rabi												
Sorghum	35,912.75	0.5046	25.94	39,520.81	0.5048	28.57	39,424.36	0.5008	27.84	40,144.00	0.5093	29.78
Pulses	19,392.10	0.5079	29.15	19,327.17	0.5154	30.30	19,412.00	0.5010	28.03	19,412.00	0.5497	36.16
Wheat	49,614.05	0.7894	395.94	70,314.83	0.7859	556.88	74,839.36	0.8110	625.54	80,147.37	0.8904	781.29
Safflower	10,242.62	0.9053	61.45	11,190.13	0.5932	30.50	13,511.02	0.8595	74.57	11,341.66	0.8608	62.75
Two seasonal												
Cotton	23,942.42	0.5142	38.11	52,656.83	0.5108	82.24	79,332.00	0.5120	124.71	79,332.00	0.5070	121.23
Total	303,772.97	6.5703	1,060.16	357,501.27	6.9082	1,491.36	391,176.17	7.1843	1,645.55	395,045.26	7.3172	1,795.91

generated, while the points shown diamonds shape represent the 20 filtered nondominated solutions. Using the Tchebycheff approach, the best-compromised solution is found for scenario-1, which is shown as square box in Fig. 2a. On choosing this point with irrigated area $f_1 = 303.772 \times 10^3$ ha and total net benefit $f_2 = 1060.16$ Million, the model readily gives the corresponding decisions at farm level and reservoir level for implementation. For this solution, Table 2, under scenario-1 gives the corresponding crop area, relative yield values and net benefits for each crop for both the seasons. Figure 3a shows the corresponding reservoir releases and storage trajectory for each time period. It can be noticed that the reservoir is not able to reach its full capacity at any time in the year, because of the far below average hydrologic condition (drought) of scenario-1. From Table 2 under scenario-1, it may also be noticed that the shortage has caused drastic reduction in the areas under all crops except pulses in the rabi season. Also for illustration purpose, the farm level decision of crop water allocations for all the crops grown in kharif and rabi seasons for each time period for this scenario-1 are shown in Fig. 4.

Scenario-2

For below-average hydrologic conditions (scenario-2), the MODE model yielded a large number of trade-off solutions between irrigated area and total net benefits, which are shown in Fig. 2b. The Pareto optimal solutions range from 310.12 × 10^3 ha, Rs 1959.91 Million, to 370.72 × 10^3 ha, Rs 1172.88 Million. This trade-off curve also indicates the nonlinear behavior of total irrigated area versus total net benefits. After computing Tchebycheff metric, the reservoir operator can decide to prefer the compromise solution shown by the square box in Fig. 2b. Then the total irrigated crop area, f_1 = 357.501 × 10^3 ha and total net benefit, f_2 = 1491.36 Million. The corresponding area, relative yield and net benefits of each crop for the preferred Pareto solution are shown in Table 2 under scenario-2. It can be noticed from this table that the irrigated area is radically different from that of scenario-1. The areas under wheat and cotton are almost doubled. The total irrigated area and net benefit have also increased with the increased water availability. In scenario-1, the water shortage is quite higher than in scenario-2, revealing that a small increase in crop area caused a severe water deficit at critical growth stages, resulting in a sudden drop in total relative yield. So, the crop area for rabi crops was suitably reduced. Figure 3b shows the corresponding releases and initial storage policy for each time period for scenario-2. It can be noticed that for scenario-2 also, the reservoir is not able to reach its full capacity at any time during the year.

Scenario-3

For the average hydrologic conditions (scenario-3), the trade-off results between total irrigated area and total net benefits are shown in Fig. 2c. The MODE is resulting in a wide variety of solutions with a minimum irrigated area of 332.17 × 10^3 ha resulting in total net benefits of Rs 2083.48 Million, and for a maximum area of 400.89 × 10^3 ha, the total net benefit is Rs 1389.33 Million. For scenario-3, after analyzing different alternatives using the Tchebycheff metric, as per his subjective judgment, if the reservoir operator chooses the solution as, f_1 = 397.176 × 10^3 ha and f_2 = Rs 1645.545 Million. The corresponding results of area, relative yield and net benefits of each crop in both the seasons are shown in Table 2 under scenario-3. The corresponding reservoir releases and initial storage policy for each time period are shown in Fig. 3c. It can be seen that the reservoir is able to reach its full capacity during the monsoon season,thus ensuring more water availability for rabi crops. The crop area for most of the crops has increased as compared to the hydrologic scenarios 1 and 2. Also the corresponding net benefits are more. As stated earlier, the MODE model also gives considerable amount of details for each point on the Pareto optimal front. For illustration purposes, typical results are presented in

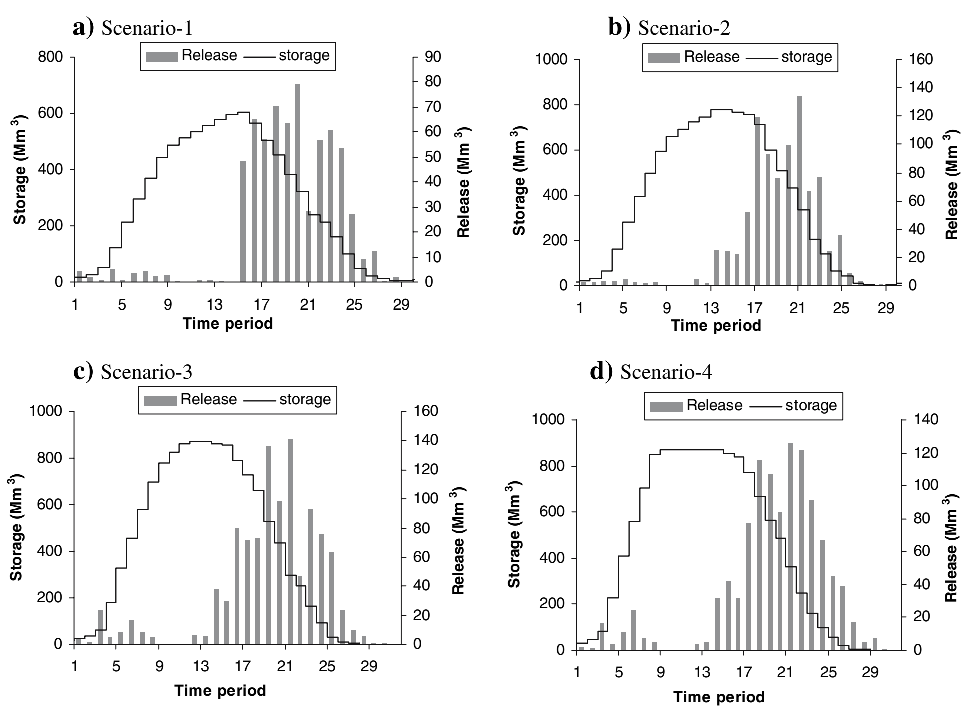

Fig. 3 The obtained reservoir level decisions for different hydrologic conditions, showing the releases and initial storages of the reservoir corresponding to the preferred Pareto-optimal solution

Table 3 Typical model results for average hydrologic conditions (scenario-3) during kharif season

Crop	Intra-seasonal time period t														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
S_t (Mm^3)	17	24.58	38.47	63.02	181.16	332.04	461.6	583.85	703.74	782.6	830.07	864.58	870	870	870
R_t (Mm^3)	4.24	1.17	21.3	5.59	7.24	15.6	7.26	4.11	0	0	0	4.14	6.68	31.91	30.7
EVP_t (Mm^3)	1.03	1.07	1.12	1.58	2.3	2.59	3.91	4.47	5.54	5.42	5.69	6.05	5.91	5.59	6.2
OVF_t (Mm^3)	0	0	0	0	0	0	0	0	0	0	0	30.23	32.57	0.2	0
$RAIN_t$ (mm)	20.9	22.1	22.0	26.3	21.6	19.9	26.5	23.8	49.3	57.6	49.0	23.4	25.5	22.5	7.2
Irrigation allocation for each period for each crop (Mm^3)															
Maize	1.536	0.584	1.668	1.328	1.236	2.803	0.793	0.569	0	0	0	0	0		
Pulses	0	0	0.383	0	0.772	0.083	0	0.153	0	0	0				
Sorghum	0.48	0	7.373	1.305	0.837	4.505	2.205	0.721	0	0	0	0			
Groundnut	0.103	0	1.226	0.16	0.775	0.408	0.632	0.612	0	0	0	0	0		
Cotton							0	0	0	0	0	2.07	3.341	15.96	15.35
AET value for each period for each crop (mm)															
Maize	27.23	26.13	37.31	31.66	31.006	34.267	37.464	31.703	37.04	34.207	33.92	22.361	23.77		
Pulses	19.06	18.29	26.34	22.35	27.358	21.417	23.415	25.028	29.242	39.608	39.276				
Sorghum	21.78	20.9	32.92	27.94	27.358	32.839	35.903	26.697	31.191	28.806	28.564	20.498			
Groundnut	21.78	20.9	32.92	27.94	27.358	28.556	31.22	33.371	29.242	27.006	26.779	20.498	21.79		
Cotton							14.049	15.017	17.545	27.006	26.779	27.952	29.71	46.81	51.174
Soil moisture at the beginning of each period for each crop (mm/cm)															
Maize	3.5	3.197	3.222	2.981	3.107	3.107	3.094	3.061	3.05	3.192	3.4	3.5	3.5	3.5	
Pulses	3.5	3.5	3.5	3.445	3.5	3.478	3.471	3.5	3.496	3.5	3.5	3.5			
Sorghum	3.5	3.456	3.5	3.408	3.433	3.373	3.297	3.254	3.262	3.439	3.5	3.5	3.5		
Groundnut	2	1.985	2	1.941	1.95	1.961	1.898	1.913	1.875	2	2	2	2	2	
Cotton							3.5	3.5	3.5	3.5	3.5	3.5	3.478	3.5	3.5
Deep percolation and surface runoff losses (mm)															
Maize	0	0	0	0	0	0	0	0	0	0	3.225	1.606	1.699		
Pulses	1.838	3.835	0	1.557	0	0	0.151	0	19.652	17.937	9.721				
Sorghum	0	0.861	0	0	0	0	0	0	0	21.766	20.433	3.469			
Groundnut	0	1.095	0	0	0	0	0	0	6.934	30.539	22.218	3.469	3.679		
Cotton							12.409	8.774	31.797	30.539	22.218	0	0.02	0	0

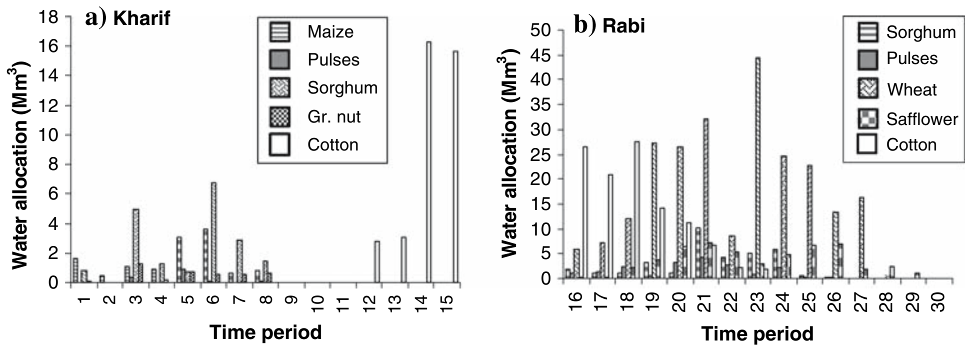

Fig. 4 The obtained farm level decisions for the hydrologic scenario-1, showing the crop water allocations (corresponding to the preferred Pareto optimal solution), for each crop in kharif and rabi seasons

Table 3, for the selected compromise solution under scenario-3.

Scenario-4

For the case of above-average hydrologic conditions, the trade-off curve between total irrigated area and net benefits is shown in Fig. 2d. Here also, it can be seen that MODE is offering a wide variety of solutions with minimum of 336.23×10^3 ha irrigated area resulting in maximum net benefits of Rs 2138.34 Million, and for a maximum area of 401.43×10^3 ha, the total net benefits are Rs 1562.08 Million. After computing the Tchebycheff metric and analyzing many alternate pros and cons, and considering individual preferences, the reservoir operator can decide to implement the policy for scenario-4, at the point indicated by square box in the Fig. 2d. Then f_1 is 395.04×10^3 ha and f_2 is Rs 1795.907 Million. The model readily gives the corresponding policy decisions at farm level and reservoir level for implementation. Table 2 also shows the area, relative yield and net benefit of each crop in both the seasons for selected policy under scenario-4. Figure 3d shows the corresponding releases and initial storages of the reservoir for each time period. It can be noticed that the reservoir is able to reach its full capacity during the monsoon season and also results in some overflows over a number of periods. These overflows will not be useful for any crop growth. So, even though considerable amounts of inflows into the reservoir and rainfall in the command area are available in the kharif season, the water available for rabi season crops has been limited by the reservoir capacity. The availability of rainwater in the dry period is also very limited (less or no rainfall/ inflows during rabi season). It may be noticed that the increase in total net benefits from scenario-3 to scenario-4 is a little, being Rs 150.36 Million, when compared with the corresponding increase from scenario-1 to scenario-2, being Rs 430.20 Million.

These results demonstrate that, the alternative solutions/ policies obtained from the multi-objective model provide good flexibility to the reservoir operator and can help in making a suitable decision for different hydrologic conditions and for different priorities accorded under the irrigation system. By effectively exploring the complex search space of the large number of decision variables and constraints, MODE captures well the nonlinear trade-off curve for the multi-objective problems. The application also proves that the MODE approach is an efficient multi-objective optimization algorithm in providing a wide spread of Pareto-optimal solutions by simultaneously evolving the irrigation planning and reservoir operation strategies. The results also suggest that changes in the hydrologic conditions over a season have considerable impact on the cropping pattern and net benefits from the irrigation system. Once the hydrologic conditions forecasted for the ensuing year are obtained by any model, the scenario corresponding to the relevant percentage of the average conditions can be chosen and the corresponding results for that scenario from the model can be directly utilized for deciding crop area, reservoir releases and allotment to each crop for each time period.

The developed methodology mainly focuses on bio-physical modeling and availability of the water as the major factor. However, in reality, other factors such as social, economic and cultural factors may also have some influence on irrigation water management practices. Here, the influencing factors include the following: social factors—governmental regulations, environmental concerns, and safety considerations; economic factors - market prices, material availability, labor cost and availability; cultural practices—planting, cultivating, fertilization, and pesticide application, etc. Apart from these factors, the size of farm holding and food habits of the local people also influence the cropping pattern in the command area. Any irrigation system is highly interdependent as the ability of individual farmers to properly utilize irrigation water is greatly influenced by the behavior of farming community in the area. Since irrigation water is a community property, participation of farmers' organizations during project formulation and implementation may play a significant role in sustainable development of the region.

In the current agricultural context, it is very important to integrate methodologies such as the one described in this study with other complementary methodologies. Thus, this paper contributes to improving irrigation planning, by developing a specific multi-objective integrated reservoir operation model for multi-crop irrigation, which helps in the decision-making process for the management and improvement of water resource usage in the reservoir command area.

Conclusions

This paper presents an efficient methodology for irrigation planning and operation of reservoir system. For multi-crop irrigation, under varying hydrological conditions, the fixed cropping pattern with conventional rule curve operating policies will have some drawbacks. To provide flexible policies, a nonlinear multi-objective optimization model is formulated for the simultaneous evolution of optimal cropping pattern and operation policies for irrigation reservoir system. The model integrates the dynamics associated with the water released from a reservoir with the actual water utilized by the crops at farm level. In order to represent the model closer to reality, it also considers nonlinear relationships for different variables in the model objective function and constraints. To obtain efficient Pareto frontiers for multiple objectives of the reservoir system, the recent multi-objective evolutionary method namely MODE is used. The applicability of the model is demonstrated through the case study of an existing irrigation reservoir system namely Malaprabha reservoir, in India. The model is applied for ten-daily reservoir operations. Multi-objective model solution includes area allocation for each crop, release from the reservoir for each time period, water allocation for each crop in each time period over a year, crop yield, net benefits, etc. To examine the sensitivity of the optimal solution to water availability, the model is evaluated for four different hydrologic conditions and their respective optimal policies are presented. The results obtained from the multi-objective model showed that the proposed MODE approach provides a wide spectra of Pareto optimal solutions, and gives sufficient flexibility to select the best irrigation planning and reservoir operation strategy. Thus the proposed methodology can be very much useful for developing efficient operating policies for multi-crop irrigation system.

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