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Crop yield optimization using genetic algorithm with the CROPWAT model as a decision support system

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ABSTRACT : Optimization problems involving on field water allocation require the integration of soil moisture balance, root growth simulation for individual crops and rainfall accounting. The FAO CROPWAT model handles all these aspects of crop development and hence this model can be utilized in such optimization problems as a means of reducing modeling complexity. A genetic algorithm based optimization model was formulated with the objective of maximizing the sum of relative crop yields of all crops under a command area considering reservoir water balance and water requirement of individual crops during different growth stages. This model was applied in an on-going river project in Assam, India. The CROPWAT model was used to estimate monthly potential evapotranspiration (PET) of crops as well as effective rainfall values at different probabilities of exceedance of rainfall and then to disintegrate these parameters into decadal (10 day) values, which were then incorporated into the optimization problem as model inputs. The performance of genetic algorithm was evaluated in comparison with the results obtained from a linear programming model. The results compared well.

KEY WORDS : Potential evapotranspiration, Actual evapotranspiration, CROPWAT, Genetic algorithm

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Irrigation management models are generally formulated with the objective of maximizing the net economic benefit from agriculture (Sethi *et al*., 2002; Karamouz *et al*., 2004; Safavi and Alijanian, 2011). In such models, the allocation of crop area and water resources is a function of the production cost and market price of different crops. But alternative objectives such as crop yield maximization may also be considered for areas where the land holding patterns are clustered and the market prices of agricultural commodities do not reflect the economic conditions of farmers. Crop yield maximization models generally apply the principle of yield response to water as described in FAO irrigation paper no.33 (Doorenbos and Kassam, 1979). Daily soil moisture accounting and root growth modeling are necessary inputs for such models (Paul *et al*., 2000; Vedula *et al*., 2005; Raul *et al*., 2012).

The CROPWAT model incorporates daily soil moisture balance, root growth, effective rainfall and deep percolation, while estimating the potential evapotranspiration and crop water requirement. This model can, therefore, be applied as a decision support tool to simplify the modeling procedure in irrigation optimization. CROPWAT has been used in various irrigation management studies for estimating crop water requirements, on-field water balance and irrigation scheduling. Kuo *et al*. (2006) used CROPWAT model to estimate the water requirements and on-farm water balance of upland and paddy crops at ChiaNan Irrigation Association, Taiwan. CROPWAT was used by Kaur *et al*. (2007) to derive optimum irrigation scheduling for wheat crops in parts of central Punjab, India. A simulation-optimzation model was developed by Darshana *et al*. (2012) using evolutionary optimization technique where CROPWAT model was employed for determining the timing and depth of irrigation to crops.

Evolutionary search algorithms, especially genetic algorithms (GAs) are gaining importance in irrigation management studies. GA optimization was used by Raju and Nagesh Kumar (2004) for evolving an optimum cropping pattern for an irrigation command. Nagesh Kumar *et al*. (2006) compared GA with linear programming (LP) for optimal of reservoir operation and concluded that GA yielded results at par with LP in maximizing crop yields. Karamouz *et al*. (2007) developed a GA based monthly conjunctive use model for supplying water according to agricultural demand with the objective of minimizing the groundwater pumping cost.

In the present study, a GA based optimization model was proposed for maximizing the relative crop yields under a command area. The model was demonstrated through its application in a case study of an on-going river project in Assam, India. CROPWAT model was used to estimate the water requirements in monthly time steps and then to disintegrate the monthly values into decadal periods, which were the inputs to the optimization model. The performance of the GA search method was evaluated in comparison with the results obtained from an LP model.

METHODOLOGY

The CROPWAT model:

CROPWAT is a decision support tool developed by the Land and Water Division of FAO for planning and management of the irrigation system (Smith, 1992). This model can be used to calculate crop water requirements and irrigation requirements on the basis of input data on crop, soil and climate. Irrigation scheduling and scheme water supply for varying cropping patterns is also possible through this model. The original model was developed in 1992 for DOS based operating systems. CROPWAT 8.0 version has been designed for WINDOWS environment, which is provided with interfaces for input data of climate, rain, crop and soil. Features like daily and decadal (10 daily) estimation crop evapotranspiration, calculation of rice water requirements using updated calculation procedures including land preparation, daily water balance output tables are some of the features of this management model.

The calculation procedures used in CROPWAT 8.0 are based on two FAO publications of irrigation and drainage series, namely, FAO 33 (Doorenbos and Kassam, 1979) and FAO 56 (Allen *et al*., 1998). The following equation describes the basic calculation procedure used in this empirical model:

$$\frac{\mathbf{y}}{\mathbf{y}_{\mathbf{max}}} = \mathbf{1 - ky}\left(\mathbf{1} - \frac{\mathbf{AET}}{\mathbf{PET}}\right) \qquad (1)$$

where, y and y_{max} are the actual and maximum yields of crop (kg/ha); AET and PET are the actual and potential evapotransiprations of crops (mm) and ky is the yield response factor.

Genetic algorithm:

Genetic algorithms (GAs) are heuristic search techniques mimicking the principles of survival of fittest and natural genetics. The search process in a GA starts with a population of random individuals and best individual is searched mimicking Darwin's principle of survival of the fittest. GAs use probabilistic transition rules instead of deterministic rules used in the classical optimization techniques (Goldberg, 1989). Three principal operations in a GA are – selection, cross over and mutation. The decision variables in GA are represented in a string structure called chromosomes. The variables can be coded in three different ways known as binary, grey or real coding. Binary representation is proposed for the present study.

In a GA, a fitness function is introduced as the performance measure of an individual string adapting to an objective landscape. A constrained problem is converted to an unconstrained problem by using the penalty function approach, which is expressed as:

$$\mathbf{P\ (x) = f\ (x) + q_n} \qquad n=1, 2, 3, ...N \qquad (2)$$

where, P(x) is the penalty function; q_n is the penalty for violation of constraint and N is the number of constraints.

The optimization model :

The objective of this study was to formulate a management model for optimally allocating water resources to different crops grown in an irrigation command during different growth stages. Hence, the objective function of maximizing the sum of relative yields of crops (Vedula *et al*., 2005) was used. It is expressed as:

$$\mathbf{Maximize\ :f} = \sum_{c=1}^{C}\left(\mathbf{1} - \sum_{g=1}^{G}\mathbf{ky}_{g}^{c}\left(\mathbf{1} - \frac{\sum_{i\in g}\mathbf{AET}_{i}^{c}}{\sum_{i\in g}\mathbf{PET}_{i}^{c}}\right)\right) \qquad (3)$$

where, C is the number of crops; G is the number of growth stages ; c, g and i are, respectively the crop, growth stage and intra-stage period indices. The inputs to this crop yield optimization model are PET and ky values of different crops during various growth stages. It is significant to note that PET values are not the depths of irrigation actually needed by individual crops during any particular growth stage. They also include the effective rainfall (ER) during that period. Similarly, AET would also consist of the actual depths of irrigation and ER. Therefore, the decision variables of this optimization problem are the depths of irrigation to be provided to each crop in decadal periods. As such, Eq.3 can be rewritten as:

$$\mathbf{Maximize\ :f} = \sum_{c=1}^{C}\left(\mathbf{1} - \sum_{g=1}^{G}\mathbf{ky}_{g}^{c}\left(\mathbf{1} - \frac{\sum_{i\in g}\mathbf{IP}_{i}^{c} + \mathbf{ER}_{i}}{\sum_{i\in g}\mathbf{PET}_{i}^{c}}\right)\right) \qquad (4)$$

where, IP is the depth of irrigation actually provided (mm). It is significant further to note that ER may sometimes exceed PET of a crop during any period. In such cases, adjustments are to be made by equating the ER with PET so that in no case, AET can exceed PET.

The constraints to the optimization model are related to reservoir water balance and water availabilty constraints.

Reservoir continuity constraint:

$$\mathbf{S_{t+1} = S_t + Q_t - R_7} \tag{5}$$

where S_t is the storage at the beginning of time t ; S_{t+1} is the storage at the end of time t; Q_t is the reservoir inflow during time t and R_t the release during time t. For simplicity, the rainfall into and the evaporation from the reservoir are not considered. The time period t is in monthly time steps. S_t, S_{t+1}, Q_t and R_t, are in units of Million cubic metres (Mcm).

Reservoir storage constraint:

$$\mathbf{S_{max} \leq S_{t+1} \leq S_{min}} \tag{6}$$

where, S_{max} and S_{min} are, respectively the maximum storage and the dead storage of the reservoir (Mcm) .

Water availability constraint:

Water requirement during any month should not exceed that water available during that month.

$$\sum_{c=1}^{C} 10^{-5} A^c IP_t^c \leq \eta_{cv} \eta_{ap} R_t \tag{7}$$

where A^c is the area under crop c (ha); η_{cv} is the conveyance efficiency and η_{ap} is the application efficiency of released water. The factor 10^{-5} is the result of unit conversion.

Model application:

The crop yield optimization model formulated in this study was applied in a case study of on-going Pagladiya dam project in Assam, India.

Study area and input data:

The proposed location of Pagladiya dam is at latitude 26°37' N and longitude 91°30' E in Baksa district of Assam. It is a multipurpose project designed to irrigate a gross command area (GCA) of about 54160 Ha on the right bank of river Pagladiya, along with an incidental power generation of 3 MW. The project is also meant for mitigating flood hazard in the downstream. This project is being implemented by the Brahmaputra Board, Govt. of India.

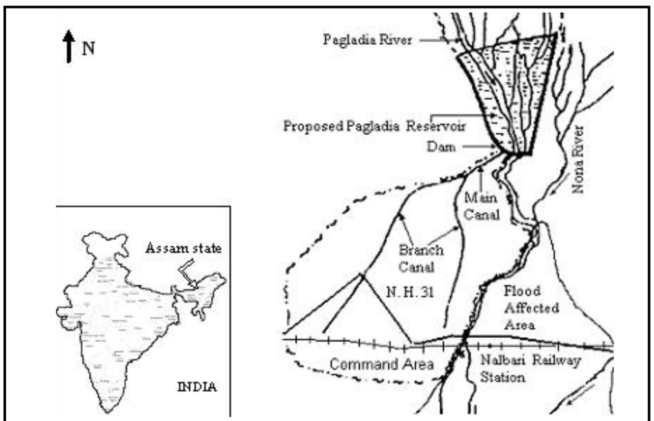


Fig. A : **Location map of the Pagladiya Dam Project, Assam, India (Adopted from Brahmaputra Board, Govt. of India)**

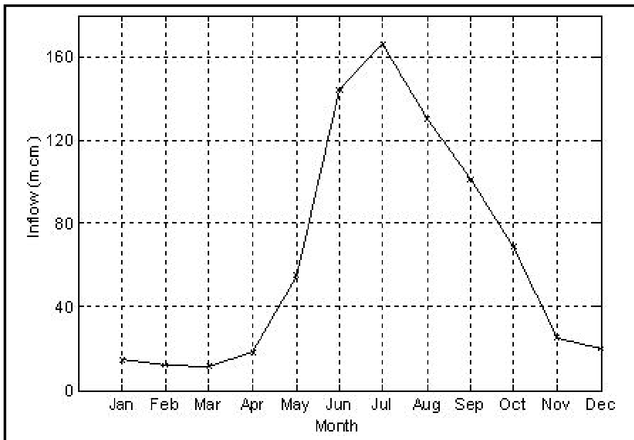


Fig. B : **Monthly average inflow at Pagladiya reservoir**

Fig. A shows the location map of Pagladiya reservoir. The reservoir is recommended for storage capacities of 45.64 Mcm, 312.64 Mcm and 472 Mcm at dead storage, full storage and maximum storage levels, respectively. A flood control reserve of 160 Mcm is recommended for this reservoir, which is the storage capacity between full storage and maximum storage levels. The hydropower generation being incidental, there is no conflicting objectives involving the project.

Reservoir inflow data for the periods 1957-1994 (Source: Brahamputra Board, Govt. of India) and 2004-2011 (Source: Water Resource Department, Govt. of Assam) were used to estimate inflow at 10%, 50% and 90% probabilities of exceedance (PE) levels so as to represent wet, normal and dry seasons, respectively, in the study area. Monthly rainfall and climatic data for 10 years (2002-2011) for the study area were collected from Regional Meteorological Centre (RMC), Guwahati. Fig. B and Fig. C, respectively show the average

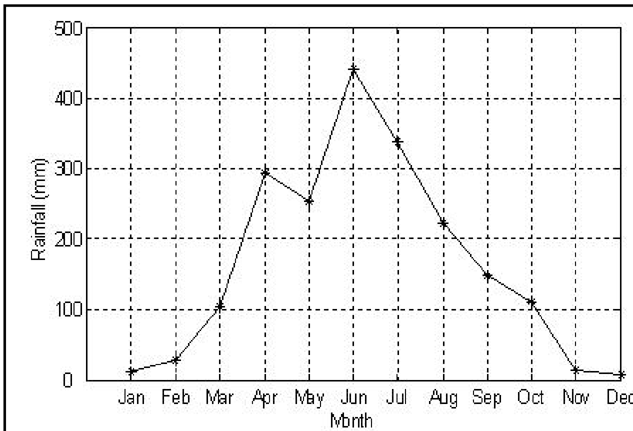


Fig. C : **Monthly average rainfall at the study area**

monthly inflow into the reservoir and the average monthly rainfall for the study area. Using the collected rainfall data, a time series of 30 years' synthetic rainfall was generated with the help of the ARIMA model (Box and Jenkins, 1976). From this time series, monthly rainfall values were obtained at the above mentioned PE levels, with the assumption that the reservoir inflow and the rainfall in the command area would follow a similar PE pattern.

Crops and cropping pattern:

The study area has a cultivable command area (CCA) of about 40743.5 ha with a net irrigable area (NIA) of about 34630 Ha. Rice is the principal crop in the state of Assam. Both summer and winter paddy, are grown in the command area. Vegetables, oil seeds, tuber crops and pulses are the other crops grown in the area. Brahamaputra Board, in consultation with the Agriculture department, Govt. of Assam has proposed a suitable cropping pattern for the irrigation command as shown in Table B.

Crop water requirement:

Crops require water mainly to meet the evapotranspirational demand. Evapotranspiration consists of evaporation from soil and transpiration from plant body. The evapotranspiration rate from a reference surface, not short of water, is called the reference evapotranspiration and is denoted as ET0. The potential crop evapotranspiration (PET) was estimated as:

$$\mathbf{PET = ET0 \times Kc} \qquad (8)$$

where Kc is the crop co-efficient.

In this study, the CROPWAT model was used to estimate both ET0 and PET. CROPWAT estimates ET0 using Penman-Monteith method (Allen *et al.,* 1998). Penman- Monteith equation can be expressed as:

$$\mathbf{ET0} = \frac{0.408(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \qquad (9)$$

where R_n denotes the net radiation (MJ/m^2/day); G the soil heat flux density (MJ/m^2/day); T the mean daily air temperature at 2 m height (°C); u_2 the wind speed at 2 m height (m/s); e_s the saturation vapour pressure (KPa); e_a the actual vapour pressure (K Pa); Δ the slope of vapour pressure (K Pa/ °C); γ the psychometric constant. The monthly climatic data for the study area along with the estimated ET0 values are presented in Table A.

The CROPWAT model has separate interfaces for input data of climate, rainfall, crop and soil. It estimates the irrigation requirements by subtracting the effective rainfall (ER) from PET. CROPWAT has the option to use four different methods of estimating ER from the input rainfall data. These are- fixed percentage of rainfall, dependable rainfall, empirical formula and the United States Department of Agriculture Soil Conservation Service (USDA-SCS) method. The USDA-SCS method was used in this study due to the fact that the estimates of ER from this method was reported to compare closely with the estimates of ER from the soil water balance method (SWBM) for well drained soil (Patwardhan *et al*., 1990). This method is explained by the following equation:

$$\mathbf{ER = Pr\left(\frac{125 - 0.2Pr}{125}\right)} \qquad (10)$$

for Pr= 250 mm or ER = 125+0.1Pr, for Pr>250 mm

where Pr is the total precipitation (mm).

The crop data required by the CROPWAT model are the crop co-efficients at different growth stages, sowing/ planting dates, duration of different crop growth stages, initial and maximum root depths and yield response factors of different crops. In case of rice, the depth of water necessary for land preparation and puddling depths also need to be specified.

The crop co-efficients depend on the changing crop

Table A : Average monthly climatic data of the study area along with the estimated ET0 values

Month	Min temp(°C)	Max temp(°C)	Humidity (%)	Wind (m/sec)	ET0 (mm/day)
Jan.	11.1	23.6	82	0.27	1.61
Feb.	13.4	27.3	69	0.41	2.25
Mar.	16.9	30.6	61	0.54	3.03
Apr.	20.7	30.4	72	0.79	3.64
May	23.3	32.2	74	0.63	3.99
Jun.	25.5	32.5	81	0.51	3.62
Jul.	26.3	32.8	83	0.47	3.46
Aug.	26.2	33.3	83	0.49	3.73
Sep.	25.4	32.8	83	0.46	3.46
Oct.	22.6	31.2	81	0.44	3.08
Nov.	17.4	28.4	80	0.33	2.41
Dec.	13.1	25.3	83	0.32	1.82

Table B : Proposed cropping pattern in the study area (Source: Brahmaputra Board)

Crop	Area (ha)	% of NIA
Rice (Winter)	20100	58.04
Rice (Summer)	16700	48.22
Wheat	1500	4.33
Pulse	3000	8.66
Potato	1800	5.20
Sugarcane	100	0.29
Jute	650	1.88
Vegetables (Winter)	1600	4.62
Vegetables (Summer)	1600	4.62
Mustard	3000	8.66
Linseed	1000	2.89
Chillies	3110	8.98
Total	54160	156.40

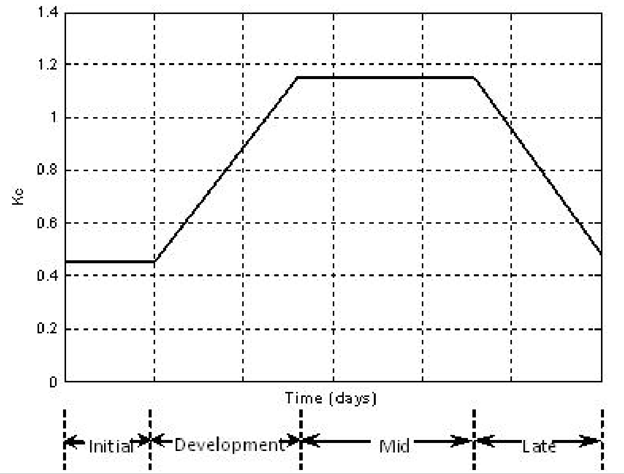


Fig. D : General trend in variation of crop co-efficients during different growth stages

Table C : Crop parameters under consideration

Crops	Sowing/ Trans. date	Duration (days)					Crop coefficient			Max. root depth (m)	Max. crop height (m)	Yield response factor			
		LP	Init	Dev	Mid	Late	Init	Mid	Late			Init	Dev	Mid	Late
Rice (winter)	15/06	30	20	30	40	30	1.05	1.20	1.05	1.00	1.00	1.00	1.10	1.32	0.50
Rice (Summer)	21/02	20	25	30	40	25	1.05	1.20	0.90	1.00	1.00	1.00	1.10	1.32	0.50
Wheat	20/11	-	15	25	50	30	0.70	1.15	0.40	1.20	1.00	0.40	0.60	0.80	0.40
Pulse	15/10	-	25	30	35	30	0.50	1.15	1.10	1.00	0.50	0.40	0.60	0.80	0.60
Potato	15/10	-	20	25	30	25	0.50	1.15	0.50	0.60	0.60	0.45	0.80	0.80	0.30
Sugarcane	01/03	-	30	50	180	60	0.40	1.25	0.75	1.50	3.00	0.50	0.75	1.20	0.10
Jute	15/03	-	25	30	45	30	0.85	1.15	0.70	1.20	2.50	0.50	0.50	1.25	0.70
Veg. (Winter)	11-Jan	-	25	30	30	25	0.50	1.05	0.90	0.60	0.30	0.40	0.80	1.20	1.00
Veg. (Summer)	3-Jan	-	25	30	35	30	0.50	1.05	0.80	0.60	0.30	0.40	0.80	1.20	1.00
Mustard	15/10	-	20	25	40	25	0.35	1.15	0.35	0.60	0.60	0.40	0.60	0.80	0.80
Linseed	15/10	-	25	30	40	25	0.40	1.15	0.40	0.70	0.70	0.40	0.60	0.80	0.80
Chillies	15/09	-	30	40	45	30	0.60	1.15	0.80	1.00	1.00	0.50	0.60	1.10	0.80

Note: Trans. = Transplanting; LP = Land Preparation; Init =Initial stage; Dev = development stage;
Mid = Mid season; Late= late season.; Veg. = Vegetables.

characteristics over the growing season. The growth stages of crops are divided into initial stage, development stage, mid season and late season. The general trend of variation of crop co-efficients during different growth stages is shown in Fig. D. Based on this curve and from available crop information, the crop co-efficients of different crops grown in the command area were estimated. Table C shows the different crop parameters and crop co-efficients of different crops. The crop parameters were chosen from related literature (Assam Agricultural University, 2009) and from interactions with the farmers of the area. In case of unavailable data, the same were taken from the FAO 56 paper (Allen *et al*., 1998).

Monthly climatic data along with soil and crop data were given as inputs to the CROPWAT model for estimating the PET values of different crops and the irrigation requirements of the crops at 10%, 50% and 90% PE levels of rainfall in decadal periods.

RESULTS AND DISCUSSION

Among the 12 crops considered in this study, it was found that summer vegetables did not require any supplementary water during all the growth periods at all the three probabilities of exceedance of rainfall. Therefore, this crop was not included in the optimization problem and so the integral measure of 11 crops were maximized. Further, the water requirements of rice during nursery and land preparation were considered to be in fixed depths. The conveyance efficiency and application efficiency of released water were considered to be 0.7 each.

In GA optimization, it is necessary to impose upper and lower limits on the decision variables. The upper limits were obtained by subtracting ER from PET. Lower limit was considered zero in all cases. GAs generally perform better with higher crossover probability and lower mutation probability. A sensitivity analysis was carried out to these two parameters in respect of the present optimization problem. In order to avoid extensive optimization during sensitivity analysis, only a single scenario of optimization *i.e.* at 50% PE level was considered. With an initial population of 100, the GA was run for 1000 generations for a set of values of the cross over probabilities in the range (0.5, 0.6, 0.7 and 0.8). The mutation probability at this stage was fixed at 0.01. The optimization model was run three times for each value of cross over probability and the best result in terms of fitness value was accepted. Results are presented in Fig. 1, which shows that the crossover probability of 0.7 yielded the best fitness. With this value of cross over probability, the GA was again run with a set of mutation probabilities in the range (0.01, 0.03, 0.05 and 0.07). The best result was shown by the mutation probability of 0.05, as evident from Fig. 1. Hence, the crossover probability of 0.7 and mutation probability of 0.05 were considered optimum for the present GA formulation.

With the optimized parameters, the GA was run for 1000 generation with an initial population size of 100. GA was run three times for each scenario of optimization *i.e.* wet, normal and dry seasons. The best results from among the three runs for all the three optimization scenarios are presented in Fig. 2. The fitness levels (sum of relative yields) show an obvious

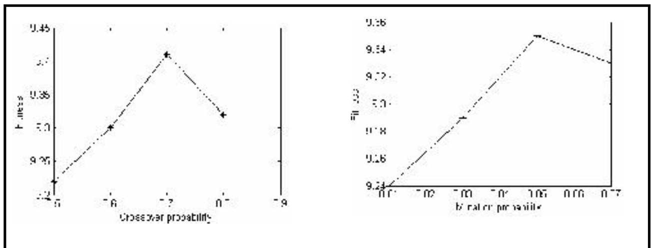


Fig. 1 : Sensitivity of GA to different user defined parameters

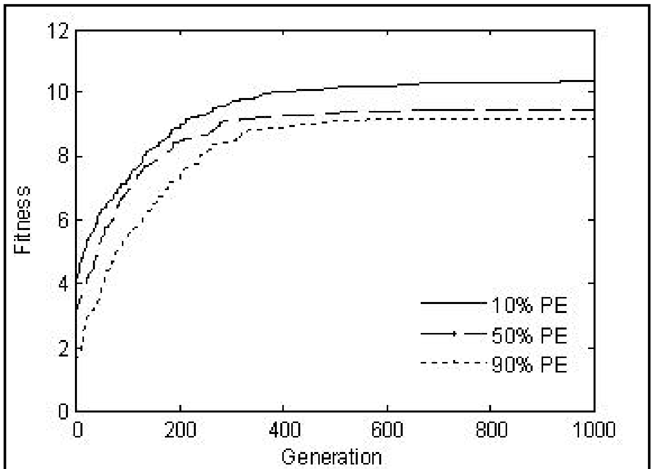
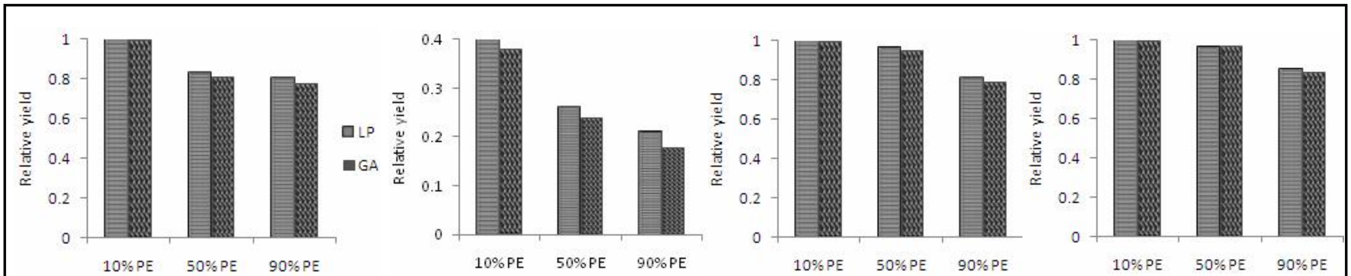
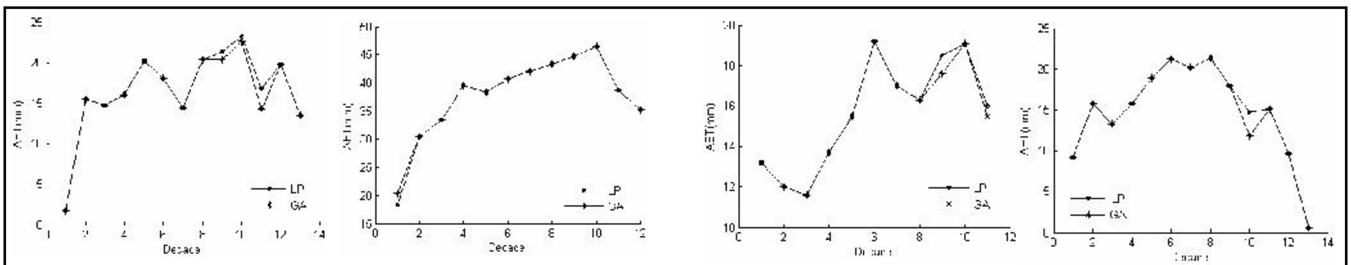


Fig. 2 : Fitness vs. Generation curves from GA optimization



(a) Wheat (b) Rice (summer) (c) Vegetable (winter) (d) Pulse

Fig. 3 : Relative yields obtained from LP and GA



(a) Wheat (b) Rice (summer) (c) Vegetable (winter) (d) Pulse

Fig. 4 : Comparative plots of AET values of selected crops during their growth stages

decreasing trend with increase in PE level. Comparative columns of relative yields of some selected crops, as obtained from LP and GA models are presented in Fig. 3, for the normal season. The results from GA compare closely with those from the LP model in most cases. Among the different crops, summer paddy showed the lowest relative yield both in case of LP and GA. This is due to the fact that this crop needs huge quantity of water for land preparation during February month, which is the driest period of the year. The AET values of few crops during their growth stages in decadal periods for the normal season, as obtained from optimization using LP and GA models, are shown in Fig. 4. The allocations are of similar pattern with occasional higher allocation by the LP model at certain instances.

Although the LP model has exhibited slightly better performance in terms of higher relative yields of different crops, certain advantages of the GA formulation can not be undermined. The GA implemented in programming platform like MATLAB has the ability to incorporate the variables and constraints easily in vectorized forms, while the problem formulation is a cumbersome task in the LP models. Moreover, the LP model permitted constraint violation in the order of 10^{-5}, while no constraint violation was permitted by the GA due to the imposition of penalty against constraint violation. A small the penalty parameter of -10 was found to be enough for this problem.

Conclusion:

A crop yield optimization model was formulated for optimal allocation of water resources to different crops grown in a command area. This model was applied in a case study of an on-going multipurpose river project in Assam. CROPWAT model was used as a decision support system to reduce the modeling complexity. The application of CROPWAT model helped in disintegrating the PET and ER values to decadal periods which are the ideal time periods for irrigation management modeling. Further, the application of CROPWAT reduced the hassles in modeling of daily moisture balance and root growth simulation, thereby simplifying the modeling procedure to a great extent.

GA optimization technique was used for solving this linear crop yield maximization problem. An LP model was also used to evaluate the performance GA. The GA formulation used in this study was found to perform at par with the LP model. The problem formulation in GA was easy as compared to the LP model. Different operators used with GA ensured that the algorithm converged to the global optimum. It may, therefore, be concluded that GA can be conveniently used in irrigation management studies.

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