  Journal of Hydroinformatics | 04.3 | 2002

Application of genetic algorithms for optimal seasonal furrow irrigation

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ABSTRACT

A quasi-optimum irrigation season calendar based on economic profit maximization for sloping and runoff-free furrows can be obtained by OPTIMEC (EConomic OPTIMization, in Spanish), a seasonal furrow irrigation model based on the concept of comprehensive irrigation. The model features four components: a soil moisture model, an irrigation hydraulic model, a crop yield model and an economic optimization module. This module uses a Genetic Algorithm (GA), a heuristic technique based on the laws of natural selection, to maximize farmer profit. The GA is a suitable technique to solve the problem of profit maximization due to the difficulties inherent in traditional optimization procedures, which require an explicit function relating flow rate, water depth and profit. For its practical application the model has been implemented in a Visual Basic program. A real case is analysed to compare the irrigation season scheduling using traditional criteria (event by event scheduling) and optimization-based criteria.

Key words | economic optimization, furrow irrigation, genetic algorithm, irrigation scheduling

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INTRODUCTION

Genetic algorithms (GA) are heuristic procedures used to obtain the maximum or minimum of unconstrained functions by utilizing random selection processes that simulate natural reproduction operators: selection, crossover and mutation. They are suitable techniques when traditional optimization procedures (e.g. linear and nonlinear programming) are difficult to apply or the very nature of the objective function prevents their applicability (Michalewicz 1994).

Economic competition amongst water users (farmers, cities, industries and the natural environment) makes irrigation management and design of the utmost importance. This importance is even greater in arid and semiarid regions, especially for surface irrigation systems, as they are one of the most water-demanding irrigation methods.

The maximum farmer profit for furrow irrigated crops can be stated on the basis of furrow design variables or management variables. Design variables are basically related to the slope and length of furrows and the shape of the cross section. Management variables include flow rate, cut-off time and irrigation date. In cases where an environmentally efficient use of water resources is also desired, the evaluation of water losses, deep percolation and runoff volumes is required. In both cases, an explicit relationship between the decision variables (design and/or management variables) and crop yield is required to estimate farmer profit. On the other hand, crop yield depends on evapotranspiration, soil conditions and the supplied quantity of water, making it increasingly more difficult to find a function which simultaneously relates all the variables involved. Different approaches to maximize farmer profit can be found in the specialized literature (Reddy & Clyma 1981; Holzapfel & Mariño 1987; Yitayew *et al.* 1985; Ito *et al.* 1999, among others).

The proposed model is based on studies by Camacho *et al.* (1999*a*) and Montesinos *et al.* (2001*b*) on sloping and runoff-free furrow systems aimed at maximizing farmer profit for the whole irrigation season according to irrigation management. A soil moisture model, a hydraulic irrigation model and a crop yield model are required to

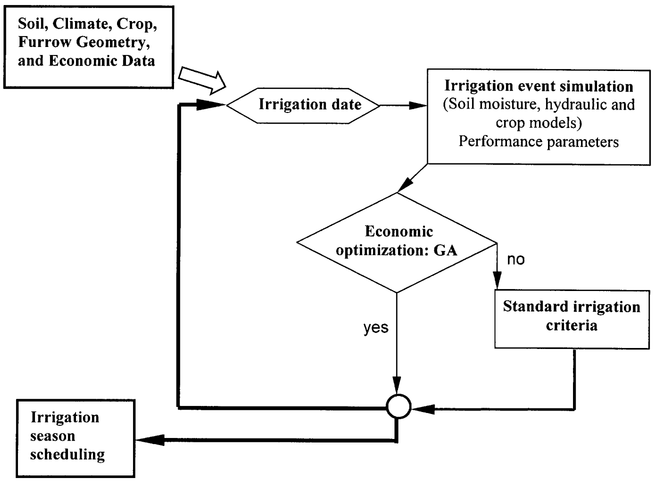

Figure 1 | Model chart.

simulate each irrigation event. The events are defined by irrigation date, inflow rate and cut-off time. By using a GA and simulated results of irrigation events, the economic optimization module obtains a quasi-optimal set of irrigation calendars that provides maximum farmer profit. GAs have been previously applied to find the best combination of management variables in furrow irrigation systems for single events (Giménez 1996). Unlike traditional optimization techniques, the nature of the GA allows for a separate estimation of farmer profit and hydraulic variables. Thus, an objective function simultaneously relating profit, water depth and flow rate is not required. A field example is used to illustrate model options and to compare the solution to the scheduling obtained by traditional criteria.

METHODS

The proposed model can schedule the irrigation season using standard criteria or an optimization based approach. For both approaches, simulation of the irrigation event is required. The main components of the model are briefly described below (Figure 1).

Irrigation event simulation

Soil moisture model

The daily evolution of soil moisture is estimated using a balance equation (Raghuwanshi 1994):

$$SMD_j = SMD_{j-1} + ET_j + P_j - I_j - Rf_j \tag{1}$$

where *SMD* is the total moisture depletion in the root zone, *P* represents the percolation, *I* is the irrigation, *Rf* is the rainfall and *ET* is the actual evapotranspiration, which is related to potential evapotranspiration values, ET_0. ET_0 is calculated by the Hargreaves equation (Hargreaves *et al.* 1985) if no recorded data are available. All these variables are in mm. Finally, *j* is a time index in days.

For single-event analysis, the irrigation dates are estimated according to the management-allowed deficit, *MAD*, which is defined as the total amount of water that a crop can extract from the soil without lowering the evapotranspiration rate. Thus, crop growing requires additional water when the soil moisture deficit is equal to or greater than *MAD*. *MAD* depends on the total available soil moisture, the storage capacity of the root zone and the wilting point, which is also related to the crop development stage, the soil and the evaporation demand (Allen *et al.* 1998).

Hydraulic furrow irrigation model

The sequence of distance–time pairs that define flow advance along a furrow is calculated using the iterative procedure proposed by Valiantzas (1997*a*,*b*), which is based on the volume balance equation and the kinematic wave model. The balance equation for a single furrow is expressed as

$$Q_0 t = \sigma_y A_0 x + \sigma_z Z_0 x \tag{2}$$

where Q_0 is the inflow rate in m^3/s, *t* is the time in s measured from the onset of irrigation, A_0 is the furrow section at inlet in m^2 calculated by the Manning equation, Z_0 is the area infiltrated at the inlet in m^3/s estimated by the Kostiakov equation, *x* is the advance distance in m and σ_y and σ_z are the shape profile factor for surface and subsurface flows, respectively. These dimensionless factors are assumed constants in the traditional models although they can vary in time. Their variation is estimated by using the kinematic-wave model.

Finally, the cut-off time is estimated assuming that recess (time required to reach every point along the furrow and to infiltrate the required depth) does not occur simultaneously along the furrow (Camacho *et al.* 1999*b*).

Performance parameters

The parameters considered to evaluate water use are as follows (e.g. Burt *et al.* 1997): application efficiency, R_a, defined as the fraction between net depth and total depth; the percolation loss coefficient C_p, is the fraction between the total applied volume and the percolated volume; the runoff loss coefficient C_r is the fraction between the runoff volume and the total applied volume. Finally, the distribution uniformity DU is the fraction between the minimum infiltrated water depth and the mean infiltrated depth.

Crop production model

The following function has been used as a crop yield estimator (Smith 1993):

$$Y = Y_{MAX} \prod_{jj=1}^{4} \left[1 - k_{Yjj} \left(1 - \frac{ET_{jj}}{ET_{Mjj}} \right) \right] \quad (3)$$

where Y is the expected yield in kg/ha, Y_{MAX} is the historical maximum yield in kg/ha, k_{yjj} is the coefficient of crop response at growing stage jj and ET_{jj}/ET_{Mjj} is the relation between the accumulated actual and maximum evapotranspiration during growing stage jj.

Economic optimization

The aim of economic optimization is to maximize net profit, NP, obtained after harvest once the irrigation season is over. Therefore:

Maximize

$$NP = YP_C - \sum_{i=1}^{k_e} (V_{wi}P_w + V_{ri}P_r + V_{pi}P_p + MO_i) \quad (4)$$

where Y is the expected crop yield (Equation (3)), P_C is the crop sale price in €/kg, V_w, V_r and V_p are the volumes in m^3/ha of applied water, runoff and percolation, respectively, P_w, P_r and P_p are the costs in €/m^3 of water, runoff collection and percolated water penalties, respectively, MO is the labour cost associated with irrigation in €/(ha event), i is the irrigation number and k_e is the total number of irrigation events in the season.

To account for the effect of surplus soil water content at the end of the irrigation season (the soil must be dry enough to facilitate crop harvesting), Equation (4) has been enlarged with an additional penalty term (Equation (5)). This term is the product of K in €/mm times $ESMD$ in mm, where $ESMD$ is the excess of soil moisture deficit over the minimum allowed value for soil moisture deficit (a result obtained of the soil moisture model) and K, the penalty cost:

$$NP = YP_C - \sum_{i=1}^{k_e} (V_{wi}P_w + V_{ri}P_r + V_{di}P_d + MO_i) + ESMD \cdot K \quad (5)$$

Genetic algorithms

A GA is a search technique for optimal solutions of unconstrained optimization problems by simulating natural selection laws (Goldberg 1989). The search starts from among an initial set of solutions which are randomly generated (initial population). The fittest solutions are then selected and modified. Any selected solution can undergo two kinds of transformations: crossover and mutation. Crossover creates new solutions by combining parts from old solutions, while mutation alters a small part of a solution. With efficient evolutionary procedures, the best partial solutions easily pass from one generation to the next. Just as in natural populations, the fittest individuals produce more offspring, spreading their genes over the next generation.

The problem stated herein is to find the set of irrigation events during the season that provides maximum farmer profit. A profit maximization approach based on traditional optimization techniques (e.g. linear and nonlinear programming or methods based on gradient calculations) is not easy due to the difficulties in establishing a continuous function which relates profit, water depth and flow rate. This can be overcome using GAs, since they work with discrete variable values that can be estimated through independent simulation procedures. In this case the hydraulic variables are estimated by simulation and then used to calculate the crop production which is the variable required to estimate the net profit or objective function. Although GAs are designed to solve discrete problems, they can easily be applied to continuous problems if the variable intervals are transformed into sets of discrete values. Other disadvantages of traditional optimization procedures include solution dependency on the initial solution and difficulties with multiple optima occurrence. These problems are avoided by using a parallel search process from a set of initial solutions which are randomly distributed throughout the solution space. Although the global optimum cannot be guaranteed, it will be hopefully in the neighbourhood of the quasi-optimum obtained. Finally, derivative calculation difficulties are also avoided by using simple transition rules through iterations.

Each irrigation event is characterized by the values of a discrete variable R and two continuous variables: H_r and Q_0, which are the required depth and the flow rate involved in the hydraulic model calculations. R is a random variable to control irrigation occurrence ($R = 0$ or 1). Commonly, the interval between irrigation events may last from 7–20 days, depending on water supply or other irrigation management circumstances. A weekly irrigation interval has been considered to simplify the problem (Montesinos *et al.* 2001*a*). Thus, combinations of feasible variable values for each week constitute an artificial individual or possible solution for Equation (5). For a w-week irrigation season, every solution is defined by $3w$ variables. Using binary coding to represent these variables, any possible solution is a string of 1s and 0s with a length of $wk_Rk_Hk_Q$, where k_R, k_H and k_Q are the number of bits that identify R,H_r and Q_0. The continuous variables are transformed into discrete ones within the intervals defined by their lower and upper bounds, $[H_{rmin}, H_{rmax}]$ and $[Q_{0min}, Q_{0max}]$. Hence, 2^{k_H} and 2^{k_Q} are the numbers of values that represent continuous intervals and are related to the desired accuracy (Wang 1991). Thus the solution searching space has $2^{\,wk_Rk_Hk_Q}$ points.

As an example, Figure 2 shows a trial irrigation season. It represents a possible solution of a w-week season, with $w = 20$ and $k_R = 1$, $k_H = 4$ and $k_Q = 3$.

From a random initial population of N potential irrigation season (e.g using a uniform distribution $U(0,1)$ generator), the GA generates a set of N modified solutions in each iteration. In general, N can vary between 20–1000, according to the number of variables involved and their accuracy (Montesinos *et al.* 1999).

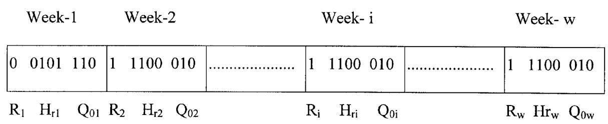

Figure 2 | Trial w-week irrigation season.

For each solution, $R_i = 1$ indicates irrigation occurrence on the first day of week i. Irrigation event simulation and soil moisture evolution for week i are required to evaluate the objective function. When $R_i = 0$, no irrigation event simulation is required but the soil moisture evolution is still needed to know soil conditions at the beginning of the following week and keep the calculations continuous throughout the season. Profit for each irrigation season is calculated by Equation (5) and is a measure of the solution *fitness*.

In Equation (5), the values of K affect the algorithm efficiency. According to Michalewicz (1994), when there is a high probability of solutions being produced which violate the constraints and inadequate penalty coefficients are used, there is a risk of creating a GA that spends more time evaluating illegal strings. When a legal solution is found in such a case, it drives the others out, the population is flooded with its offspring and better solutions are not found. Hence a sensitivity analysis is required to determine the appropriate value of penalty coefficients for each particular problem (Montesinos *et al.* 1999).

Once solution fitness is calculated, the fittest solutions are selected to make up a new population of solutions. The selection operator used (Montesinos *et al.* 1999) ranks the solution strings in increasing order according to their fitness (Figure 3(a)). The least fit strings are then eliminated and subsequently replaced by the duplicates of the fittest solutions in order to maintain the population size. The replacement order is shown in Figure 3(b). The solutions of intermediate fitness remain in their initial positions. Thus, the highest fitness solutions, their duplicates and the intermediate ones make up the mating

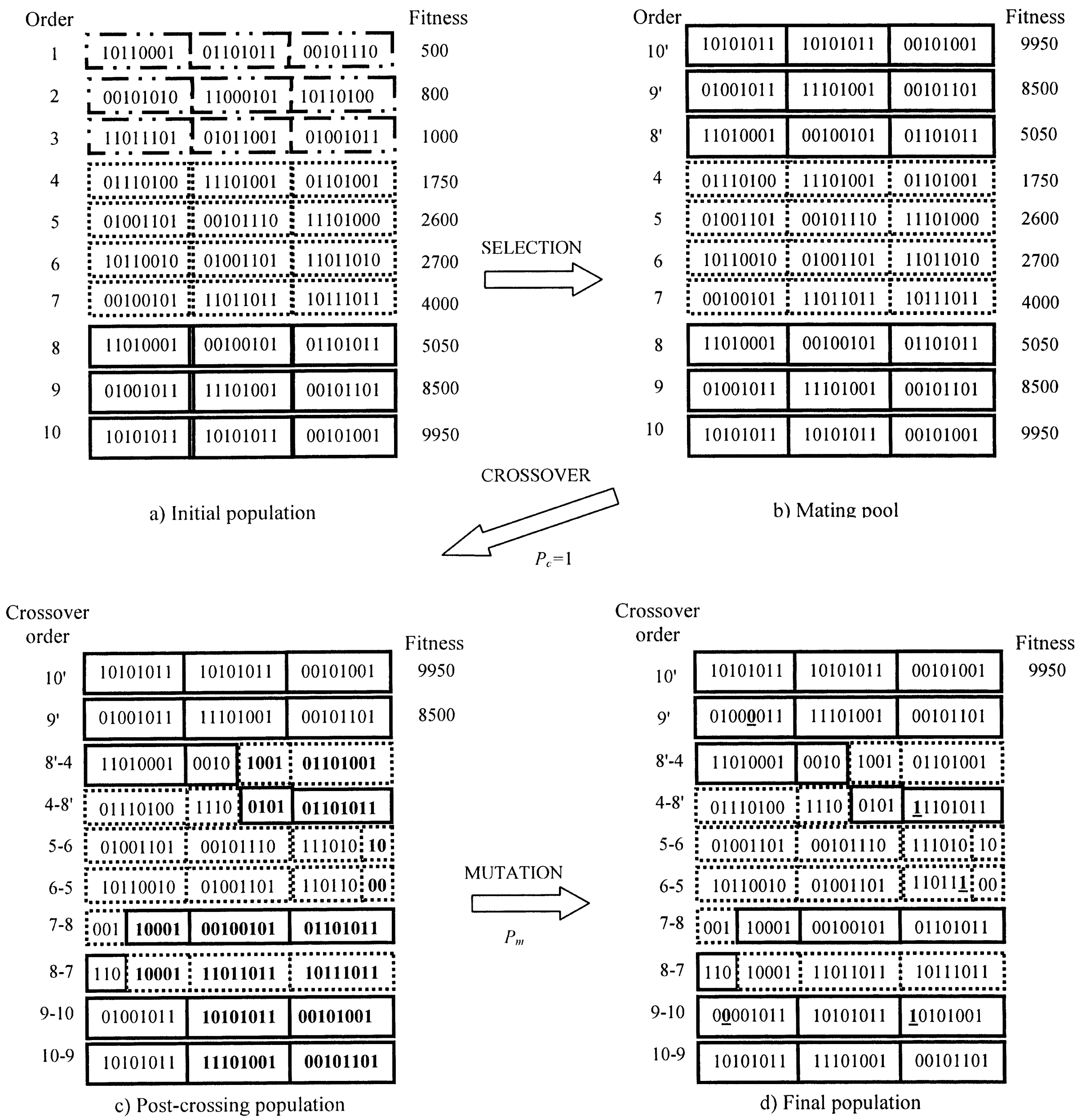

Figure 3 | Genetic operators. Boldface points out bits changed by crossover and mutation. Long- and short-dashed lines indicate worst solutions, dotted lines indicate intermediate solutions and full lines indicate best solutions.

pool. They all exceed a certain fitness threshold (Figure 3(b)). In accordance with their positions, every solution but the first and the second is mated and crossed with the next, with a crossover probability of 1 (Figure 3(c)). A one-point crossover scheme is used. As is shown in the previous figure, the crossing point is randomly chosen from among the parent strings and the bits after this point are exchanged between them. In this way, the features of the two best irrigation seasons are saved in the next generation.

These deterministic selection procedures encourage solution pairs of similar fitness to be obtained. Thus, selection of the worst irrigation calendar and the excessive repetition of the fittest is avoided while intermediate schedulings that may be ameliorated in subsequent generations are maintained. The ranking of the survival strings and their subsequent pairings helps to yield better offspring by combining solutions according to their positions.

To fix the number of solution to be eliminated and duplicated, a new variable, n_l, associated with each string is defined as follows:

$$n_l = [Nsi_l] \quad l = 1, \ldots, N \tag{6}$$

where $[a]$ represents the rounded integer of a, N is the population size and si_l is a selection index per string. It is only computed at the beginning of the process. This term is based on the selection probability defined by Wang (1991). We have decided to use the term *selection index* rather than *selection probability* as this process operates in a deterministic way.

The selection index of the lowest fitness solution, si_1, and that of the highest, si_n, are

$$si_l = \frac{2-c}{N}; \qquad si_n = \frac{c}{N} \tag{7}$$

where c is a parameter that ranges in (1.5,2). The selection index for the remaining solutions, si_l, are linearly interpolated between si_1 and si_n. For any values of c, n_l takes the values 0, 1 and 2. When n_l is equal to 0 (worst solutions), the solution is eliminated. When it is equal to 1 the solution remains (intermediate solutions), and when n_l is equal to 2 (best solutions), the string is duplicated.

The parameter c controls the percentage of individuals eliminated or duplicated. A sensitivity analysis has been performed to determine the optimal values of c (Montesinos 1995). c values from 1.6–2 have been tested, yielding percentages of eliminated strings from 8.3–25%. The present GA does not show a considerable sensitivity to c. It has been fixed at 1.8 as the highest profit irrigation seasons obtained in the sensitivity analysis were for values around 1.8. $c = 1.8$ means that the new population to be crossed is made up of 18.8% duplicated solutions, 18.8% eliminated solutions and 62.45% intermediate solutions.

The final stage of the GA is the *mutation* process, which occurs with some specified mutation probability, p_m, for each bit of the solutions obtained by crossing. The mutation operator changes the value of the selected bit to the opposite value (i.e. 0 to 1 or 1 to 0). To avoid destroying too many ameliorated solutions, it normally takes small values, between 0.001–0.01 (Goldberg 1989; Wang 1991; Liong et al. 1995). For a given value of p_m, the mean number of mutated bits in a population of N solutions is $wk_Rk_Hk_QNp_m$. This average can be obtained using different procedures (Montesinos et al. 1999). This number is obtained by generating random numbers in the intervals [2 and N] and [1, $wk_Rk_Hk_Q$] to choose the string and the bit to be modified, respectively. This mutation scheme maintains the best solution unaltered and also allows at least one mutation to occur per selected solution (Figure 3(d)).

The number of generations, G, to achieve populations which are principally made up of *good solutions* is also related to the solution string length and generally varies between 50–500 generations. The best irrigation season is stored in every iteration. Therefore, the final solution is the highest profit irrigation season scheduling found through successive iterations. While the nature of GAs does not guarantee this solution to be the global optimum, our experience has demonstrated that it will be in the neighbourhood.

RESULTS

The theoretical concepts described above are implemented in a Visual Basic 5.0 application, whose structure is shown in Figure 4. The data are introduced through different program screens or by the database file Irrigation.mdb, which is also the output file and can be read by or exported to commercial database software.

Program description

OPTIMEC allows either the analysis of single irrigation events or the scheduling of the whole irrigation season

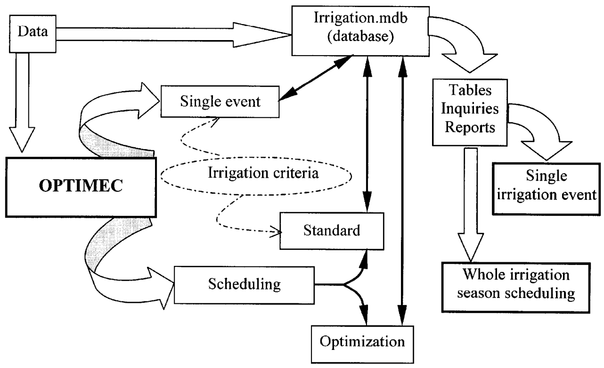

Figure 4 | OPTIMEC operation chart.

if the economic optimization module is applied. The scheduling alternatives are:

- *Standard scheduling or event by event scheduling.* (1) Irrigate at a certain flow rate and water depth, if the soil moisture deficit equals or surpasses the *MAD*. (2) Irrigate at a certain flow rate and water depth if the soil water deficit equals or surpasses a limit fixed by the model user. (3) Irrigate at a certain flow rate and water depth during a fixed time interval.
- *Optimized scheduling*. Irrigate randomly in weekly intervals. Water depth and flow rate are transformed into discrete random values chosen between certain minimum and maximum bounds. A GA based optimization procedure determines the optimum weekly irrigation sequence.

Irrigation database file

Three types of data structures make up the Irrigation.mbd file: *tables* (three input data tables for Crop, Soil and Climate information and four result tables for Crop Coefficients, Moisture Balance and Optimization information); *inquiries* (the user enquires from one or more tables according to set criteria about Irrigation Scheduling, Advance and *ET*) and *reports* (to show datasets and permit the introduction or modification of values for Advance/Infiltration, *ETa/Etmax*, Crop Coefficient and Scheduling).

Real case

A real irrigation case is studied next in order to demonstrate the applicability of OPTIMEC. The irrigated field is located in Córdoba, southern Spain (38°N, 5°W, elevation: 110 m) in the middle of the Guadalquivir River Valley. It is a typical Mediterranean location with erratic annual rainfall distribution and long dry summers. The input data are the same as those involved in the models described above (e.g. crop, ET_o, furrow geometry and economic data). In the present version, ET_o values (recorded at the study location or calculated separately) are entered in a simple table (day-value in mm).

To schedule the irrigation season for the maize field the following assumptions are considered: the soil moisture deficit at sowing time was zero; the infiltration rate and the geometry of furrow sections are constant in time and space; furrows are uniform in slope and runoff free; *MO* are 0.185 €/ha per event and P_c is 0.15 €/kg, common values in the area. Two approaches can be compared: a standard approach and a genetic algorithm optimization based approach.

Standard scheduling

This option depends greatly upon the irrigation criterion selected. The field will be irrigated when the soil moisture deficit, *SMD*, is greater than the *MAD*. It is also assumed that the expected deficit at the end of the irrigation season is equal to or greater than half of the field capacity moisture content to avoid harvesting problems (90 mm according to the soil characteristics (Camacho *et al.* 1999*b*)). Following the second standard irrigation criterion, it has been assumed that the required infiltrated depth, H_r, is 0.9*SMD* and that the flow rate ranges from 1.5–2.5 l/s. Soil moisture is evaluated every day. The mean values of the performance indexes R_a, C_r, C_p and *DU* are displayed in Figure 5 simultaneously for the whole season versus irrigation cost per hectare. Water cost has been fixed at 0.006 €/m^3 (common price in the area) and no runoff or percolation costs have been considered for the present study.

Lower costs and higher values for the irrigation performance indexes are achieved for an incoming flow

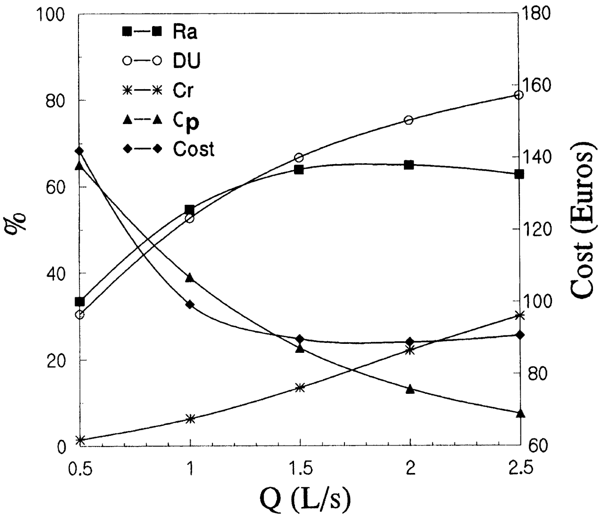

Figure 5 | Sensitivity to flow rate variability in a standard irrigation scheduling.

rate of 2 l/s. The model allows schedules to be analysed for a wide range of flow rate values and selects the flow rate according to the highest application efficiency criterion. The scheduling report for the inflow rate, $Q_0 = 2$ l/s, is shown in Table 1, where irrigation date, event number, cutoff time, t_{co} and soil moisture deficit the day prior to irrigation SMD_b are also given. At the end of the season the crop yield was 10 215 kg/ha at 90 €/ha with a profit of 1449 €/ha.

Economic optimization of the irrigation season

GA optimization determines the quasi-optimal weekly scheduling for the maize field described above while maintaining the initial assumptions. The maize cycle lasts approximately 150 days and it has been grouped into 21 irrigation weeks. The variables involved are: R, H_r and Q_0. The last two variables are transformed into discrete variables. The intervals for H_r are [10 mm, 115 mm] and [0.5 l/s, 2.6 l/s] for Q_0. The bounds are established based on practical values and the upper bound for Q_0 is fixed according to erosion limits (Koluveck *et al.* 1993). The variables are binary coded, H_r has 4 digits and Q_0 has 3. Hence, the string length is 168 bits (8×21) and $2^{168} \approx 3.74 \times 10^{50}$ points make up the solution space. The GA evolves from a random initial population of string solutions and modifies them through several generations to derive a new set of solutions. Finally, the maximum profit irrigation schedule is selected from among this set.

OPTIMEC users must fit the GA parameters to each particular problem. For the problem stated in this paper, Camacho *et al.* (1999*a*) considered the following GA parameter values to be adequate after performing several sensitivity analyses: 500 solutions per population, 70 generations and 0.005 as mutation probability.

Solutions are selected according to Equation (5). The sensitivity of the procedure to the cost of exceeding a threshold of maximum allowable soil moisture content, *K*

Table 1 | Standard irrigation scheduling report

Date	Event	H_r (mm)	Q_0 (L/s)	T_{co} (min)	SMD_b (mm)	R_a	C_r	C_p	DU
13-Jun-98	1	97.18	2	185.92	108.0	0.65	0.24	0.11	0.77
27-Jun-98	2	90.21	2	173.43	100.2	0.65	0.22	0.13	0.75
10-Jul-98	3	89.35	2	171.97	99.3	0.65	0.22	0.14	0.74
22-Jul-98	4	86.92	2	167.88	96.6	0.64	0.21	0.15	0.74
04-Aug-98	5	89.00	2	171.37	98.9	0.65	0.21	0.14	0.74
19-Aug-98	6	95.39	2	182.62	106.0	0.65	0.23	0.12	0.77

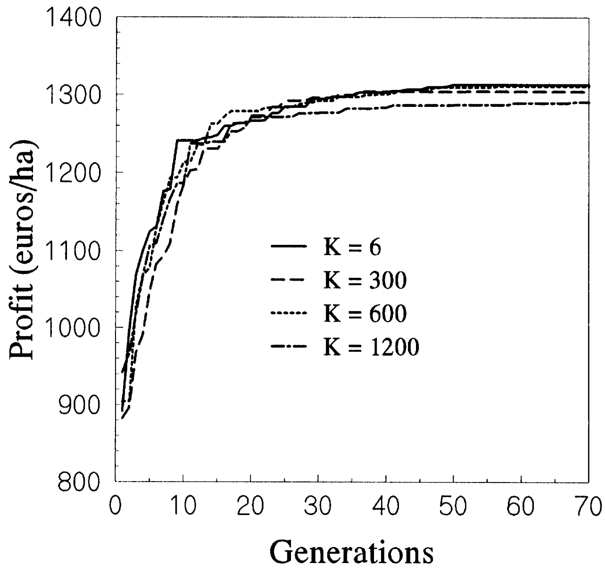

Figure 6 | GA sensitivity to *K* variation for a 500 solution population.

€/mm of exceeding moisture, is displayed in Figure 6. While there are no remarkable profit differences among the *K* values studied, the differences would probably be larger if the scheduling were extended to include the whole crop field instead of a single hectare. Maximum profit is obtained for the lowest *K* value, showing that higher penalties may overload good solutions with penalty costs and avoid their selection.

Several optimization runs with $K = 6$ €/mm, water costs from 0.006–0.12 €/m^3, runoff and percolation costs from 0–0.06 €/m^3 are displayed in Figures 7(a, b). The costs are similar to those proposed in the literature (Ito *et al.* 1999). R_a maximum values are obtained for the highest penalty costs for the whole range of water prices, giving lower applied depths per year.

Table 2 shows the scheduling report when the price of water is 0.006 €/m^3 and no penalty terms are considered for comparison with the standard option results (runoff and percolation losses are linked to the selected inflow rate). It is clear from Table 2 that H_r, Q_0 and the number of irrigation events are random values. Although the new irrigation sequence is more costly (160 €/ha), crop yield is higher (11 857 kg/ha) and the profit (1626 €/ha) is also greater than in the standard scheduling case.

Several OPTIMEC runs have been carried out to study the influence of percolation and runoff economic penalties in the optimization process. Profits achieved are

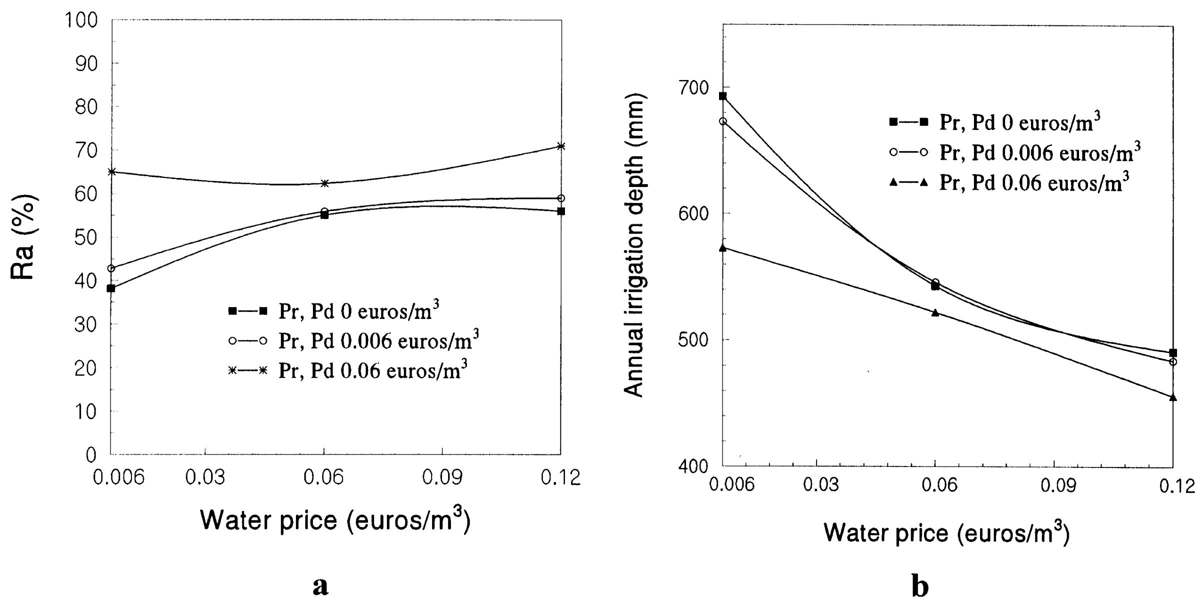

Figure 7 | (a) *Ra* sensitivity to water, runoff and percolation costs; (b) annual supplied depth sensitivity to water, runoff and percolation costs.

Table 2 | Optimised scheduling report

Date	Event	H_r (mm)	Q_0 (L/s)	T_{co} (min)	SMD_b (mm)	R_a	C_r	C_p	DU
07-May-98	1	24	2.3	78.09	15.7	0.20	0.11	0.70	0.34
28-May-98	2	45	2.6	82.77	34.8	0.36	0.17	0.46	0.57
04-Jun-98	3	38	2.3	86.02	24.3	0.28	0.12	0.61	0.49
11-Jun-98	4	38	2.6	77.40	30.6	0.34	0.16	0.50	0.50
18-Jun-98	5	45	2.3	91.39	38.9	0.42	0.13	0.46	0.55
25-Jun-98	6	52	2.3	97.70	42.9	0.43	0.14	0.43	0.61
02-Jul-98	7	59	2.3	104.97	43.8	0.41	0.16	0.43	0.66
09-Jul-98	8	52	2.3	97.70	44.0	0.44	0.14	0.42	0.61
16-Jul-98	9	66	2.3	113.19	45.9	0.40	0.18	0.42	0.70
23-Jul-98	10	66	2.6	104.57	46.7	0.39	0.23	0.38	0.71
30-Jul-98	11	66	2.3	113.19	44.7	0.39	0.18	0.43	0.70
06-Aug-98	12	52	2.3	97.70	43.1	0.43	0.14	0.42	0.61
13-Aug-98	13	59	2.3	104.97	42.1	0.39	0.16	0.45	0.66
20-Aug-98	14	31	2.6	72.96	39.1	0.46	0.15	0.39	0.43

higher than for the standard option (e.g. $P_w = 0.0006$ €/m^3, $P_r = 0.006$ €/m^3, $P_p = 0.006$ €/m^3, profit = 1578 €/ha).

DISCUSSION

The results obtained by the GA (with and without percolation and runoff costs and penalizing water excess at the end of the irrigation season) provide higher profits than standard scheduling. Water surplus at the end of the season, percolation and runoff costs can also be computed after each irrigation event for standard scheduling. However, in this case, the model user cannot control these profit penalizations. Instead, the optimization option provides a maximum profit irrigation calendar, which simultaneously considers all problem constraints. Thus, without runoff and percolation penalties the GA based option represents a 12% increase in profit compared to the standard option. A 9% profit increase is reached even when the penalized GA results are considered. For a 10 ha irrigation field (common size in the study area), the farmer obtains an additional profit of 1770 or 1290 € per harvest (without and with runoff and percolation costs, respectively). Thus, the optimization option may aid in planning water use within the framework of sustainable development and implies a long-term benefit for farmers while preventing both aquifer and stream contamination by nitrates and sediments, respectively, and then maintaining their waters within the water quality standards.

CONCLUSIONS

The proposed model obtains either an irrigation season scheduling that maximizes farmer profit or a traditional scheduling for different irrigation criteria. Economic profit maximization for the irrigation season as a whole has been stated on the basis of a GA. For this option, runoff and percolation losses and an excess of soil deficit moisture at the end of the irrigation season are economically penalized. These penalties have been considered in order to find a solution, which not only provides the highest profit (greater than the standard option), but also maintains optimal harvesting and environmental conditions (efficient water use, low sediment production and low aquifer contamination rate). Economic evaluation of the environmental impact of irrigation runoff and percolation excess is needed to determine the exact point at which both economic and environmental interests can be considered simultaneously. The GA described above efficiently solves the complex maximization problem posed, making OPTIMEC an important tool in planning water use within the framework of sustainable development.

NOTATION

GA	genetic algorithm
SMD	total moisture depletion in the root zone
P	percolation
I	irrigation
Rf	rainfall
ET	actual evapotranspiration values,
ET_o	potential evapotranspiration
j	time index in days
MAD	total amount of water that a crop can extract from the soil without lowering the evapotranspiration rate
Q_0	inflow rate
t	time measured from the onset of irrigation
A_0	furrow section at inlet
Z_0	area infiltrated at the inlet
x	advance distance
σ_y	shape profile factor for surface flow
σ_z	shape profile factor for subsurface flow
R_a	application efficiency
C_p	percolation loss coefficient
C_{2r}	runoff loss coefficient
DU	distribution uniformity
Y	expected yield
Y_{MAX}	historical maximum yield
k_{yjj}	coefficient of crop response at growing stage jj
ET_{jj}/ET_{Mjj}	relation between the accumulated actual and maximum evapotranspiration during growing stage jj
jj	growing stage index
NP	net profit
P_C	crop sale price
V_w	volume of applied water
V_r	volume of runoff
V_p	volume of percolation
P_w	cost of water
P_r	runoff collection penalty
P_p	percolated water penalty
MO	labour cost associated with irrigation
i	irrigation index
k_e	total number of irrigation events in the season.
$ESMD$	excess of soil moisture deficit over the minimum allowed value for soil moisture deficit at that time of the irrigation season
K	penalty cost when $ESMD$ is not equal to 0
H_r	required depth
R	random variable which controls irrigation occurrence
w	irrigation season duration in weeks
k_R	number of bits that identifies R
k_H	number of bits that identifies H_r
k_Q	number of bits that identifies Q_0
N	number of potential irrigation season analysed in each iteration
$U(0,1)$	uniform distribution
n_l	variable which fixes the number of solution to be eliminated and duplicated
l	string index
si_l	string selection index
si_1	selection index of the lowest fitness string
si_n	selection index of the highest fitness string
c	parameter required to calculate the string selection index
p_m	mutation probability
G	number of generations
t_{co}	cutoff time

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