GLOBAL OPTIMIZATION OF DEFICIT IRRIGATION SYSTEMS USING EVOLUTIONARY ALGORITHMS

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Abstract

Water is a limited resource and the dramatically increasing world population requires a significant increase in food production. For improving both crop yield and water use efficiency, the usual optimization strategy in irrigation at the field level considers scheduling parameters, i.e. when and how much to irrigate, as well as control parameters, i.e. the intensity and the irrigation time, for each water application. Optimizing control and schedule parameters in irrigation is considered as a nested problem. The objective of the global optimization is to achieve maximum crop yield with a given, but limited water volume, which can be arbitrary distributed over the number of irrigations. It is difficult to solve the global optimization problem, because the target function has many locally optimal solutions and the number of optimization variables, i.e. the number of irrigations is unknown a-priori. For this reason, a made to measure evolutionary optimization technique (EA) is employed to find a near-optimal solution of the global optimization problem within acceptable computational time. The results provided by the new optimization strategy are compared with the popular shuffled complex evolution algorithm (SCE-UA) optimization algorithm, simulated annealing (SA) and differential evolution (DE). The comparison demonstrated a striking superiority of the new tool with respect to both the achieved irrigation efficiency and the required computational time.

1. Introduction

Agriculture is still the greatest water user of all while having the lowest water use efficiency. Especially, irrigated agriculture is particularly guilty of inefficient water use, the pollution of ground and surface water and land degradation. Thus, good water management practices in irrigation aim to improve water use efficiency, along with preserving the soil and water resources, without sacrificing crop productivity.

When irrigation is constrained by limited water availability, a maximum crop yield is not achievable. With deficit irrigation, the plants are consciously under-supplied with water and a reduced crop yield is accepted as the penalty. For example corn reacts positively on deficit irrigation and the penalty in harvest terms is slight compared to the generous benefits in water saving. However, each plant's level of water stress sensitivity fluctuates with respect to its different growth phases. For this reason, when laying down the irrigation schedules for an entire growth period, it is important to decide beforehand when the growth phases requiring generous irrigation water volumes will occur and, on the other hand, when smaller volumes will suffice. The success of an irrigation plan depends on (i) an appropriate – crop requirement oriented – dividing up of the season's entire water irrigation volume between the different irrigation events (irrigation scheduling), and (ii) a spatially homogeneous distribution of the prescribed water volume over the field at each irrigation event (irrigation control).

In literature we can only find a few approaches with respect to the global optimization of irrigation scheduling. These efforts are generally limited to identifying irrigation schedules on the basis of a "sensor-controlled" irrigation strategy using water balance modeling as for e.g. CROPWAT [13]. On the basis of such approaches, the relevant studies demonstrate that a successful irrigation control is possible with respect to the scheduling of a simple deficit irrigation strategy. However, because the efficiency of single irrigation cycles can only be estimated, their respective inter-dependency with the irrigation scheduling is not able to be fully taken into account. [9] presents an approach based on fixed intervals between the irrigation cycles for solving this problem with respect to furrow irrigation. Bearing minimal water consumption in mind, both the optimal inflow and the irrigation time are evaluated using a grid search for each single irrigation. Unfortunately, this approach does not allow achieving a global optimal irrigation scheduling due to the subjective fixing of the irrigation times and because of failing to pay sufficient attention to the inter-dependency between the single irrigation events. [1] introduce a global approach for optimal irrigation scheduling on the basis of dynamic programming. In order to maximize the harvest, they propose an optimal distribution of a given total amount of water for a single irrigation cycle. However, dynamic programming necessitated a substantial reduction in the complexity of the problem. The investigation was therefore based on a regular interval between the single irrigation events and the discretization of the used water balance model was relatively coarse. A further measure for reducing the computational effort consists in selecting an extremely simple harvest model, which, however, fails to take into account the interconnection between the different growth periods and the varying stress sensitivity of the plants. Such simple harvest modeling is criticized by [10] who proposed, as an alternative, a 2-step optimization in order to limit the computational effort arising from the use of a more complex harvest model. A further development of the approach proposed by [14] avoids separating the optimization process. Moreover, daily irrigation decisions allow optimizing the amount and date of the different irrigation events. The main disadvantage of the optimization strategies proposed by [1], [10] and [14] lies in the necessary discretization of the water transport models and, more specifically, of the soil moisture content. This seriously limits the predictive reliability of the models, which, in turn, affects the schedules and, thus, causes substantial problems as regards the optimal control of single irrigation events. Optimal irrigation control requires a reliable simulation of the surface flow, as well as a rigorous portrayal of the soil conditions. However, due to the growing complexity, this cannot be achieved by dynamic programming.

A new strategy presented in this contribution overcomes these restrictions by rigorous process-based seasonal irrigation modeling together with an evolutionary optimization technique, which accounts for both variable irrigation intervals and variable irrigation parameters.

2. The nested optimization problem in deficit irrigation

Optimizing both the control and schedule parameters in deficit irrigation is treated as a nested problem: (i) optimizing the control parameters for each single water application, which is referred to as the "inner optimization" and (ii) optimizing the irrigation schedule (i.e. the number as well as dates and water volumes of the water applications) over the whole growing season, which is referred to as the "outer optimization". The objective of the global (nested) optimization is to achieve maximum crop yield Y with a given, but limited, water volume V_0, which can be arbitrarily distributed over a number of irrigations. The impact of different irrigation schedules on the crop yield is calculated by a process-based irrigation seasonal model. The given global optimization problem is then:

$$\mathbf{max}\; Y(\mathbf{S}) \;:\quad \mathbf{S} = \{\mathbf{s}_i\}_{i=1\ldots n} = \{(t_1, V_1, q_1)\,,\,\ldots,(t_i, V_i, q_i)\,,\,\ldots,(t_n, V_n, q_n)\} \qquad n, t_i \in \mathbb{N};\; V_i, q_i \in \mathbb{R} \tag{2.1}$$

with the optimal solution for maximizing the yield Y:

$$\mathbf{S}^* = \mathbf{arg\,max}\; Y(\mathbf{S}) \tag{2.2}$$

where $\mathbf{S}$ is the schedule for a whole growing period consisting of $i = 1 \ldots n$ irrigations each defined by the date t_i, the irrigation depth V_i, and the inflow rate q_i. Now suppose that this problem is partitioned into schedule and irrigation control subproblems by partitioning the vector of the system parameters $\mathbf{s}$ into two vectors, $\mathbf{s}_s$ and $\mathbf{s}_c$, of the schedule and irrigation control variables:

$$\mathbf{S} = \{\mathbf{s}_i\}_{i=1\ldots n},\;\; \mathbf{s}_i = \{(\mathbf{s}_{s,i}, \mathbf{s}_{c,i})\}_{i=1\ldots n},\;\; \mathbf{s}_{s,i} = (t_i, V_i),\;\; \mathbf{s}_{c,i} = q_i. \tag{2.3}$$

Nested optimization subsequently solves two optimization problems:
the **outer** optimization problem:

$$\{\mathbf{s}_{s,i}\}^*_{i=1\ldots n} = \mathbf{arg\,max}\; Y\left(\left\{(\mathbf{s}_{s,i}, \mathbf{s}^*_{c,i}\right\}_{i=1\ldots n}\right) \;\text{ and} \tag{2.4}$$

a number of n **inner** optimization problems:

$$\mathbf{s}^*_{c,i} = \mathbf{arg\,max}\; AE^{lq}(\mathbf{s}^*_{s,i}, \mathbf{s}_{c,i}) = \mathbf{arg\,max}\; AE^{lq}((V_i^*, \bar{\theta}_i(t_i^*), q_i)\;\; i = 1 \ldots n. \tag{2.5}$$

The outer loop (Eq.2.4) maximizes the yield Y of the plant with respect to n irrigations, with control parameters optimized for each of the irrigation events. The inner optimization (Eq.2.5) finds the optimal flow rate q_i^* with respect to a high low quarter application efficiency AE^{lq} (see [2]) for the ith irrigation event with an initial soil moisture $\bar{\theta}_i$ at an optimal date t_i^* and irrigation depth V_i^* generated by the outer optimization loop.
The outer optimization has the specific feature that the number of optimization variables, i.e. the number n of irrigation events $\mathbf{s}$, is a-priori unknown. Three constraints are subsequently established in order to determine a set of feasible schedules. The application in deficit irrigation requires

$$\sum_{i=1}^{n} V_i \leq V_0, \tag{2.6}$$

i.e. the sum of the irrigation depth for each water application must not exceed a given water volume V_0. Secondly, the time between two irrigations $\mathbf{s}_i$ and $\mathbf{s}_j$ may not fall below a minimal value t_{min}

$$\mathbf{abs}(t_i - t_j) \geq t_{min} \text{ for } \forall t_i, t_j \in \mathbf{S};\ \ i \neq j \tag{2.7}$$

in order to exclude schedules with an unusually high frequency of water applications which tend to result in high costs for labor and the maintenance of the irrigation system. On the same basis as above, each irrigation depth is restricted to a minimal irrigation depth V_{min} per water application

$$V_i \geq V_{min}. \tag{2.8}$$

3. The basic strategy for solving the nested irrigation problem

It is difficult to solve the global optimization problem, because the target function has many locally optimal solutions and features an undefined number of optimization variables because the number of irrigations is a-priori unknown. Thus, finding the global solution is not possible with classical deterministic optimization techniques. For this reason, our strategy combines evolutionary algorithms, artificial neural networks and rigorous process modeling for substantially improving irrigation efficiency. A made to measure evolutionary optimization technique (EA) is employed to find a near-optimal solution of the outer optimization problem (when and how much to irrigate) within acceptable computation time. For efficiently solving the inner optimization problem, i.e. the determination of the control parameters for each water application (intensity), a problem adapted artificial neural network (ANN) based on self-organizing maps (SOM-MIO) was developed. The SOM-MIO portrays the inverse solution of a coupled numerical irrigation model and, thus, enormously speeds up the overall performance of the complete optimization tool. For training the SOM-MIO with realistic scenarios we apply the seasonal furrow irrigation model (FIM) which comprises process-based simultaneous modeling of the 1D surface flow, the quasi-3D soil water transport, and the crop growth. The model is based on an analytical zero-inertia surface flow model iteratively coupled with the numerical code HYDRUS-2D, which simulates subsurface flow by the modified Richards-Equation. In addition to the obtained accuracy, this also permits the consideration of soil evaporation and precipitation as well as root water uptake by plants.

4. Methods

4.1. **The seasonal furrow irrigation model.** A seasonal furrow irrigation model (FIM, see [16]) is used to simulate water flow of subsequent irrigation applications as well as the redistribution time between two applications. Surface flow during irrigation advance is based on the analytical solution of the Zero-inertia differential equations [11]. Simplifications of the surface flow equations are used for storage, depletion and recession phases, where an uniform flow regime is assumed at the tail end of the furrow. A model assumption is free draining flow in arbitrary shaped furrows with a constant inflow rate. Cross-sectional infiltration is calculated at not necessary equidistant computational nodes along the furrow and integrated over the wetted furrow reach. Surface and subsurface flow is coupled by an Newton iterative scheme. Infiltration is calculated by the numerical code HYDRUS (Version 2.0, [15]), which solves the Richards-equation for flow in two-dimensional variably saturated soil. A sink term for water uptake by plant roots is already integrated in the code. Root depth is assumed to increase linear with time until

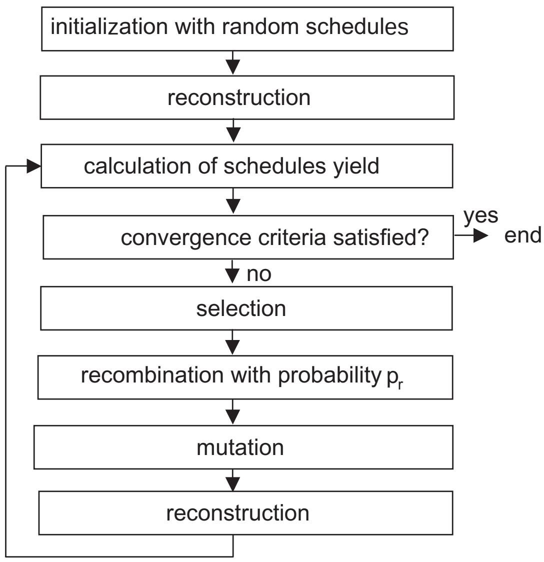


FIGURE 4.1. Flowchart of the algorithm for the optimization of irrigation schedules.

a maximum depth is reached, which is generally associated with the time of the potential leaf area index-maximum. Root water-uptake activity increases exponential with depth as described by [8]. Evaporation is considered from the soil surface which also takes into account the changing type of the upper boundary condition at the surface calculation nodes during irrigation (prescribed flux prescribed head and vice versa). Crop growth is simulated by prediction of daily leaf area index using the principles outlined in [7] and water stress index calculated from the transient moisture content in the root zone.

4.2. **Solving the complex optimization problem in irrigation scheduling with a tailor-made evolutionary algorithm.** The basic structure of the evolutionary algorithm is shown in Fig.4.1. It deviates in certain aspects from the standard operators – selection, recombination and mutation – of evolutionary optimization algorithms. These deviations include, firstly, a change in the order in which the individual operators are dealt with. During each single generation step the selection becomes the first operation to be carried out instead of coming at the end. By doing this, it becomes possible to neglect additional function evaluations within the initialization; this results in a decrease in the overall number of the necessary function evaluations. Secondly, an additional reconstruction step for exploiting already available knowledge, in order to be able to guarantee compliance with the complex constraints. The implementation of the operators in brief is:

Selection: Due to the fact that the selection takes place in the search space only on the basis of the value of the objective function – i.e. without taking the inner structure or the position of the individuals into account – it is quite a straightforward matter to adopt the already proposed selection strategies. For this purpose we rely on the Tournament selection.

Recombination: Due to the fact that the number of irrigated events can differ between the two parent individuals, it is not possible to directly adopt one of the standard recombination operators. Instead, the recombination operator must be altered to suit the structure of the data. Because plant water uptake is time dependent, with respect to recombination it makes sense to stick with the relationship between the irrigation time and volume of the schedules which were assigned to the two parents. This can be achieved by creating the offspring individual out of a selection of irrigation tuples, which themselves are chosen from the combined total of the parents own irrigation schedules.

Mutation: For all the irrigation times t_i and irrigation volumes V_i of an irrigation schedule, the mutation takes place by adding a normally distributed random parameter, which has to be freshly determined for each variable to be mutated. Different crops react differently to changes made in the irrigation timing and /or in the irrigation water volumes. For this reason, with regard to the controlling of the mutation, a distinction is made between the variances for the mutation of the irrigation times and between the variances for the mutation of the irrigation volumes.

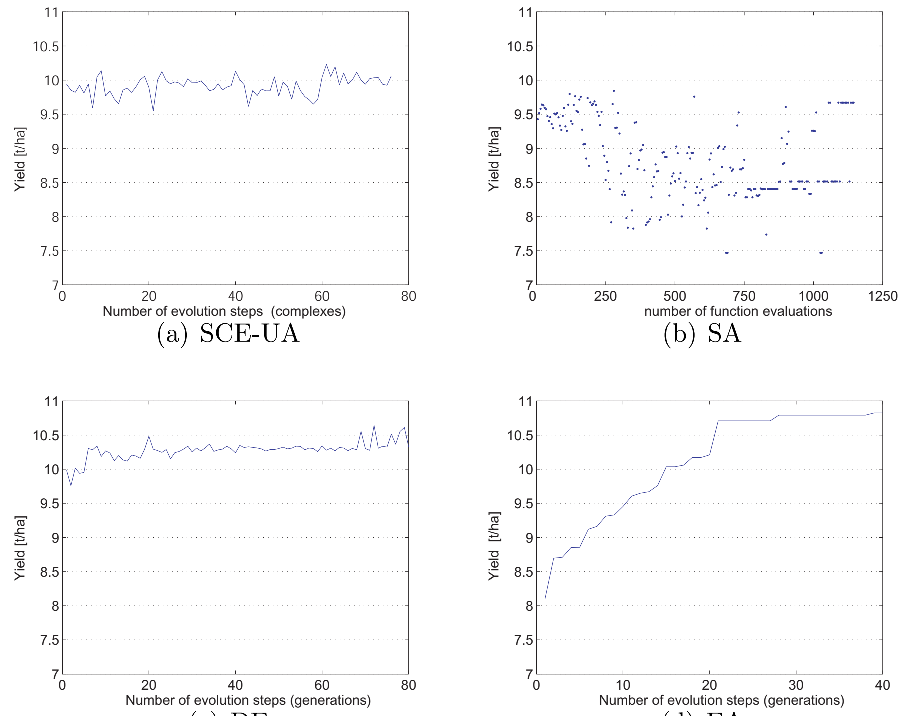
Reconstruction: Schedules of the new population are reorganized in the following manner: two water applications with an irrigation interval smaller than a given minimal irrigation interval are combined to one water application. The water volume of both water applications are added and the irrigation time of the first event is fixed for the resulting water application. All the other water applications remain in the schedule without changes. Thereafter the amount of each water application is normalized to meet the total available water volume with the sum of the single irrigation water volumes.

After the prescribed steps are applied to the whole population, one generation of an EA is completed. The algorithm iterates until a certain desired degree of convergence is reached. EAs usually require many function valuations for convergence (computational time) because they don't use derivative information of the objective function. But the presented EA in this context combines the flexibility to restrict the parameter space to valid solutions with the possibility of an extensive parallel processing.

4.3. **Using neural networks for transferring the complex physically based irrigation model into a simple tool for irrigation control.** Originally, self-organizing maps (SOM) are used as a tool for solving classification problems [5]. In order to open a wide range of application in water resources [12] expanded the SOM principle by generating multiple continuous output information after the standard training procedure. During application the resulting new SOM-MIO architecture arranges data vectors consisting of input and output data into two predefined parts in accordance with the underlying problem. Rearranging the original data vectors allows switching between different mapping functions which are provided by the SOM-MIO.

5. Application of the nested optimization strategy to furrow irrigation

For analyzing the performance of the new optimization strategy, we compared four approaches, namely the new strategy with an evolutionary algorithm (EA), differential evolution (DE, [6]), simulated annealing (SA, [4]), and the shuffled complex evolution algorithm (SCE-UA, [3]) on the base of a numerical experiment. In the subsequent analysis DE, SA, and SCE-UA solve a simplified optimization problem, where the number and



(a) SCE-UA (b) SA

(c) DE (d) EA

FIGURE 5.1. Comparison of the convergence behaviour of different optimization algorithms.

date of the irrigation events are taken to be the same as the result of the EA optimization. This simplification is necessary because both optimization algorithms cannot handle optimization problems with a varying number of optimization variables as occurring in the considered realistic experiment. In order to solve the global optimization problem all the optimization algorithm got the support of the SOM-MIO for solving the inner optimization problem.

5.1. **The irrigation scenario.** In a real case application a limited amount of $50\,m^3$ water had to be distributed with an optimal irrigation schedule to gain maximum crop yield. In our experiment simulated by FIM, corn is grown over a growing period of 132 days. The irrigated field is a 130m long plot of silty loam, characterized by the slope $S_0 = 0.0025\,m/m$ and the roughness $K = 25m^{1/3}/s^{-1}$. Five vertical infiltration sections of 0.8 x 5.0 m homogeneous soil are located at x_{inf} = [0, 32.5, 65.0, 97.5, 130.0 m] and imposed by an initial matrix pressure of $-30\,m$. The soil hydraulic parameters of the van-Genuchten model are: $\theta_s = 0.38$, $\theta_r = 0.05$, $\alpha = 1.5\,m^{-1}$, $n = 1.46$, $m = 1 - 1/n$ and saturated hydraulic conductivity $K_s = 3.9 \cdot 10^{-6}\,m/s$.

5.2. **Results and conclusions.** Except for the differential evolution in the case with the prescribed irrigation times, not one of the procedures succeeds in achieving the crop yield attainable by the EA-algorithm. The relatively poor yields which were achieved even with the considerably simplified optimization problem are – as seen in Figure 5.1 – a consequence of the poor convergence behaviour of the other methods in the investigation. The optimization runs were stopped after 1600 functional evaluations if the investigated optimization procedures hadn't already converged to a solution. An extensive trial & error search for appropriate parameters of the optimization algorithm yielded no success in the case of SA and SCE-UA. With the one exception of the proposed specialized irrigation optimization algorithm - which can ascertain for itself when, how often and how much to irrigate – not one of the optimization procedures is capable of improving on the irrigation schedule which was prescribed at the outset. The result demonstrated a striking superiority of the new strategy with respect to both, the achieved yield and the convergence of the optimization. In addition, the success of the evolutionary algorithm shows that it is advantageous to incorporate knowledge about the problem structure when dealing with complex optimization problems such as process-based simulation based control and scheduling of irrigation systems.

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