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# Predictive Irrigation Scheduling Modeling in Nurseries

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Additional information is available at the end of the chapter

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## Abstract

Water requirement allocation plays an important role in modern farming management. Evapotranspiration-based irrigation controllers can ideally provide irrigation according to the water requirements of the plant. This chapter describes predictive irrigation scheduling in nurseries with multiple crop species and high-frequency water requirements under limited resources. Based on historical data, time-series analysis is used to forecast evapotranspiration, an essential element in water balance equation. An algorithm based on a hierarchical research including dispatching priority rules and taking into account crop characteristics, available water, and constraints of the hydraulic network is proposed to predict irrigation schedules, with the objective of minimizing crop's water stress periods and optimizing resource materials. Simulation results with different climatic conditions show on the one hand the ability of the time-series model to forecast potential evapotranspiration, and on the other hand that, given a typical nursery, the proposed predictive approach of irrigation scheduling compared to the non-predictive approach makes it possible to prevent crop's water stress.

**Keywords:** multiple crops, high-frequency irrigation, multiobjective optimization, evapotranspiration forecasting, time series

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## 1. Introduction

Accurate scheduling of irrigation is essential for maximizing crop production while conserving water and ensuring irrigation systems that are environmentally and economically sustainable. Effective scheduling requires good knowledge of crop tolerance to stress, crop water demand, and soil water characteristics. Water availability is one of the most critical factors in the determination of plant survival. The cost of water today represents a relatively large percentage of overall production costs. Moreover, environmental policies now tend to

limit excessive use of water [1]. Various methods and tools for irrigation scheduling listed below have been developed, ranging from those based on the water status of the soil or plant, to those that use a model to estimate soil water balance. Irrigation control has been carried out using different time scales and different approaches.

In Ref. [2], a time-threshold model is defined as the expected daily amount of time that a crop exceeds its temperature threshold when humidity does not limit cooling of the canopy through transpiration, to detect a water-stressed condition and to signal the need for irrigation. In Ref. [3], a distributed irrigation control system with autonomous wireless controller units used soil water potential measurements to control the amount of water applied to each specific area of a field, and measurements of the system's hydraulic pressure to communicate together. A comparison of the performance of an irrigation-control tray method (extensively used in greenhouses for plants grown in bags for horticultural production) adapted to the specific conditions of plants grown outdoors in containers, to the tensiometric method was carried out in Ref. [4]. In both methods, irrigation was stopped after a fixed time (2–4 min, depending on the growth phase), and new irrigation cycles were not initiated for the next 120 min. This study concluded that the plant biomass was not significantly different between the two methods and that the irrigation events were comparable. In Ref. [5], a prototype of a real-time smart sensor for irrigation scheduling in cotton crop of four different management zones on weekly basis is developed. In the same area, [6] evaluated the precision of soil moisture sensors for irrigation control to measure the volumetric soil water content. The study conducted in Ref. [7] concluded that continuous monitoring measurements of trunk diameter fluctuation (TDF) could be used for irrigation scheduling in young olives tree under intensive production. TDF measurements under variable water regimes have now been published for some fruit tree species (apple and peach, [8] and mature peach trees [9]).

Authors in Ref. [10] were the first ones to develop an irrigation-scheduling program using meteorological data to calculate water use; many variations of this approach are now in use. Ref. [11] presented a study of a daily forecasting system of irrigation water requirements that can provide management support for administrators in terms of water supply and water distribution in irrigation schemes. The system is formulated by using the fuzzy theory based on analysis of water management logic that is based on the administrator's experience and knowledge. Using the results of field tests, they showed that the strategy for forecasting primarily depends on the intuitional and the creative judgment of administrators. In Ref. [12], a simple spreadsheet model uses a water-budgeting approach to schedule irrigation of a eucalyptus plantation. Their model estimated plantation water use on the basis of a pan coefficient (the ratio of water use to pan evaporation), and measured pan evaporation using the Penman-Monteith (P-M) equation. Their model calculated daily changes in soil water and salinity level by tracking various components of the water balance, and enabled the user to design an irrigation schedule by predicting future irrigation requirements based on the current rate of water use. To enable model users to estimate water use without the need for detailed climate data and complex evapotranspiration models, monthly pan coefficients were derived for 33 reference sites within 10 biogeoclimatic zones across Australia. In Ref. [13], irrigation scheduling with an automated evaporation pan system is performed using automated measurements of evapotranspiration (ET) from a screened pan. The crop evapotranspiration

is accumulated hourly in a residual. The residual is compared hourly to the user-set irrigation threshold before irrigation is called for. In Ref. [14], the ability of three brands of ET-based irrigation controllers for irrigation scheduling in a standard residential landscape is analyzed in comparison with a theoretical model of soil water balance. They used a daily soil water balance model to estimate the theoretical irrigation needs and compare the latter with the actual amounts of water applied. Other irrigation methods are based upon empirical approaches, usually derived from the visual aspect of the plant and sometimes using sensors and time controllers to monitor watering. No prediction of crop water requirements is taken into account in most of these approaches. The control unit usually reacts to changes and perturbations in the environmental parameters of the nursery area.

Sustainable irrigation aims to match water availability and water needs in quantity and quality, in space and time, at reasonable costs and with acceptable environmental incomes [15]. Triggering in advance irrigations in horticultural nurseries with limited material resources could improve the production quality. In this way, water requirement forecasting could be helpful. Thus, predicting the evolution of crop water needs in a nursery area is essential to maintain the production under control and to ensure crop safety. This aspect is more particularly cogent in horticulture where short-term variations of local weather conditions may modify evapotranspiration. This variation has to be anticipated to prevent water stress. In a similar way, [16] proposed a hybrid approach combining a simplified crop transpiration model to predict the necessary water supply and water flow measurements from the crops. This approach was used to iteratively adapt the model coefficients. A crop transpiration model was then used to predict water supply and water flow measurements, while a simple model was used to adapt the model coefficients.

The diversity of container nursery production is different from any other faced of agriculture. The sizes and shapes of plants and containers, number of plant species and cultivars, methods of irrigation delivery, fertilizer types and application methods, and the number of plants per unit area make container production a very complex problem [17]. Substrate containers have a low storage capacity, crops have a high water requirement during sunny periods, and water contents fluctuate rapidly; that is why very specific watering methods should be applied to irrigate containers in horticultural nurseries. Continuous dripping systems are currently on the rise. Because evaluations of the water content of the substrate once a day are not sufficient, daily weather data afford the opportunity to react quickly to weather changes. Real-time weather data can provide information based on recent potential or reference evapotranspiration ( $ET_0$ ) rates. Moreover, irrigation networks usually supply only a limited number of plots because the main line has a limited capacity; this makes irrigation control complex for nursery workers. Water availability is the most crucial factor for plant survival and development. Consequently, water requirement forecasts are valuable tool for irrigation management.

The primary objective of irrigation decision making is to apply enough water so plant growth is not restricted. Minimizing leaching by monitoring container drainage and adjusting irrigation scheduling accordingly is not the primary objective for most growers at this time. Few growers are using BMPs (best management practices) such as ET-based irrigation scheduling, tensiometers, or other systems of objective irrigation scheduling [17]. Simulation models would use local weather to help growers with BMP decision making, including irrigation and nutrient scheduling.

In a former study [18], an example of irrigation triggering based on  $ET_0$  prediction was presented. Results with two experimental plots showed noticeably that most of the irrigation events of the predictive triggering took place earlier than in the nonpredictive triggering. This chapter focuses on large-scale multiple crops nurseries, with high-frequency irrigation requirements under limited water availability, with the objective of scheduling simultaneous irrigation requests of the crops. The chapter is divided into two parts. The first part is devoted to  $ET_0$  forecasting. It first describes the SARIMA (Seasonal AutoRegressive Integrated Moving Average) structure model used in time-series analysis, and then presents identification of the model coefficients and the validation results. The second part focuses on the predictive irrigation scheduling. The main structure of the scheduling algorithm is then presented and is followed by the comparison of simulation results between the nonpredictive irrigation-scheduling and the predictive irrigation-scheduling approaches.

## 2. $ET_0$ prediction

Evapotranspiration is defined as the evaporation from a soil surface and the transpiration from plant material [19]. Reference ET is described as the ET from a hypothetical reference crop with the features of an actively growing, well-watered, dense green cool season grass of uniform height. Many equations are available in the literature for  $ET_0$  estimation. The most precise one accepted by the international scientific community is the Penman-Monteith (P-M) equation for its good results compared with other equations in various regions worldwide [19].

The FAO-56 PM equation for the hourly time step reads as follows:

$$ET_0 = \frac{0.408\Delta(Rn - G) + \gamma\left(\frac{37}{T_{hr} + 273}\right)u_2(e^0(T_{hr}) - e_a)}{\Delta + \gamma(1 + 0.34 u_2)} \quad (1)$$

where  $e_a$  is the actual average hourly vapor pressure (kPa),  $e^0(T_{hr})$  the saturation vapor pressure at  $T_{hr}$  (kPa),  $U_2$  the average hourly wind speed ( $m s^{-1}$ ),  $T_{hr}$  the mean hourly air temperature ( $^{\circ}C$ ),  $\gamma$  the psychrometric constant ( $kPa \ ^{\circ}C^{-1}$ ),  $G$  the soil heat flux density ( $MJ m^{-2} h^{-1}$ ),  $Rn$  the net radiation at the grass surface ( $MJ m^{-2} h^{-1}$ ),  $\Delta$  the slope of the saturation vapor pressure curve at  $T_{hr}$  ( $kPa \ ^{\circ}C^{-1}$ ), and  $ET_0$  is the reference evapotranspiration ( $mm hr^{-1}$ );

$ET_0$  gives a potential evapotranspiration value issued from modeling. The relationship between that derived value and the exact amount of water required by the plant depends on the crop coefficient, that is, a biometric parameter that varies with the crop species and its growth stage (height of the aerial part).

### 2.1. Model structure

Using reference evapotranspiration  $ET_0$  as an indicator for triggering irrigation can offer an advantage for nursery workers since mixed-farming irrigation control is hard to tackle. A few studies deal with evapotranspiration forecasting using time-series analysis. In Ref. [20], time-series modeling was investigated to forecast the monthly reference for crop evapotranspiration. Paper [21] proposed a daily irrigation-scheduling algorithm based on ET prediction. An

ARIMA (AutoRegressive Integrated Moving Average) model was also used in Ref. [22] to forecast daily and hourly references for evapotranspiration. In the latter study, the analysis evidenced a wide scattering of calculated versus forecast values, especially for hourly values.

The accurate forecasting of  $ET_0$  in nurseries based on prevailing meteorological conditions could lead to an efficient management of plot-valve opening. Although meteorological centers have a huge computational power, the weather forecasts used to calculate  $ET_0$  are only accurate on a regional scale, with lower performance at the local scale. Such poor performance can be explained by the fact that current weather forecasting uses 10-km wide coarse elementary square meshes. Thanks to the recent developments in supercomputers and observing systems, the results from the latest research in numerical prediction of weather systems achieve meshes between 4 and 2.5 km wide in the national weather services of a limited number of European countries [23].

In order to compute hourly  $ET_0$ , a climatic database with four types of measurements (global radiation, air temperature, relative humidity, and wind speed) was used. The meteorological parameters were made available every 10 min. At the end of each hour, a computation of  $ET_0$  was obtained by averaging these six measurements. As the wind velocity is one of the most difficult parameters to forecast accurately, the reliability of the forecast using physically based equation was reduced. Thus establishing a separate model for each component of the climatic data would have led to uncertainties in the final  $ET_0$  value.

Like the four climatic data elements it is based on,  $ET_0$  can be considered as a time series because it corresponds to a set of  $N$  successive random observations  $x_1, x_2, \dots, x_N$ , performed at a specific frequency.  $ET_0$  can also be regarded as a specific outcome of a statistical process. Most time series are stochastic in that the future is only partly determined by past values; as a result, it is impossible to reach exact predictions: they have to be replaced by the notion that the probability distribution of future values is determined by past values.

The original time series had a 24-h periodicity that corresponded to the normal evolution of the meteorological parameters, more particularly radiation that plays determining role in  $ET_0$  estimation. This periodicity allows for well-adapted SARIMA models as compared to the AR (Auto Regressive), MA (Moving Average), and ARMA models we also tested. In these models, results are not accurate enough, and there are too many parameters to be estimated. The SARIMA model integrates seasonal fluctuations; we used the estimation procedure suggested by Ref. [24] in this context.

The general multiplicative SARIMA model of order  $(p,d,q) \times (P,D,Q)_s$  is defined as follows:

$$\phi_p(B) \Phi_p(B^s) \nabla^d \nabla_s^D Z_t = \theta_q \Theta_q(B^s) a_t \quad (2)$$

where

$$\nabla = 1 - B \quad (3)$$

$$\nabla_s = 1 - B^s \quad (4)$$

$\nabla$  is the differencing operator,  $\nabla_s$  is the seasonal differencing,  $B$  is the backward shift operator.  $a_t$  is a purely random process (corresponding to a zero-mean Gaussian white noise with

variance  $\sigma_e^2$ ),  $Z_t$  and are formed from the sampled original series at time  $t$ ,  $S$  is the period of the series,  $d$  is the ordinary differencing order, and  $D$  is the seasonal differencing order.  $\phi_p$ ,  $\Phi_P$ ,  $\theta_q$  and  $\Theta_Q$  are polynomials in  $B$  of order  $p$ ,  $P$ ,  $q$ , and  $Q$ , respectively, which fulfill the stationarity and invertibility condition.

$P$  and  $Q$  are the degrees of the autoregressive and moving average seasonal polynomials,  $\Phi$  and  $\Theta$ ,  $p$  and  $q$  are the degrees of the autoregressive and moving average polynomials, respectively. The time-series model requires identification of the functional form of the model, and then the model parameters can be calibrated with sample data sets.

## 2.2. Identification and validation

The selected model is expected to forecast the next value of  $ET_0$ , based on past measurements. The forecast model was obtained by the iterative strategy of specification, estimation, and checking. Thus, the development of a time-series-forecasting model must be done in an iterative fashion, in which (1) the form of the forecasting model is predicted, (2) the coefficients of the model are estimated, and (3) the errors of the forecasting model are analyzed. Steps 1, 2, and 3 are repeated until the errors of the forecasting are reduced to white noise with no significant correlation. More precisely, the time-series model requires the identification of the form of the model, and then the model parameters can be calibrated to the identification sample data.

The values of  $p$ ,  $P$ ,  $q$ , and  $Q$  were thus assessed by studying the autocorrelation function (acf) and the partial autocorrelation function (pacf) of the differenced series, and by choosing a SARIMA model where acf and partial acf had a similar form Refs. [24–28]. By analyzing the acf and the partial acf of  $ET_0$ , the general form of the forecasting model was developed, then the coefficients of the model estimated and the errors forecasting model were analyzed. The values of  $d$ ,  $D$ ,  $p$ ,  $q$ ,  $P$ , and  $Q$  were computed from the Statgraphics-plus software package, whereas the Matlab package was used to develop the computer program for the validation process. From the model structure (0,1,0)(0,1,1)<sub>24</sub>, developed in Ref. [18], the final value of the prediction was

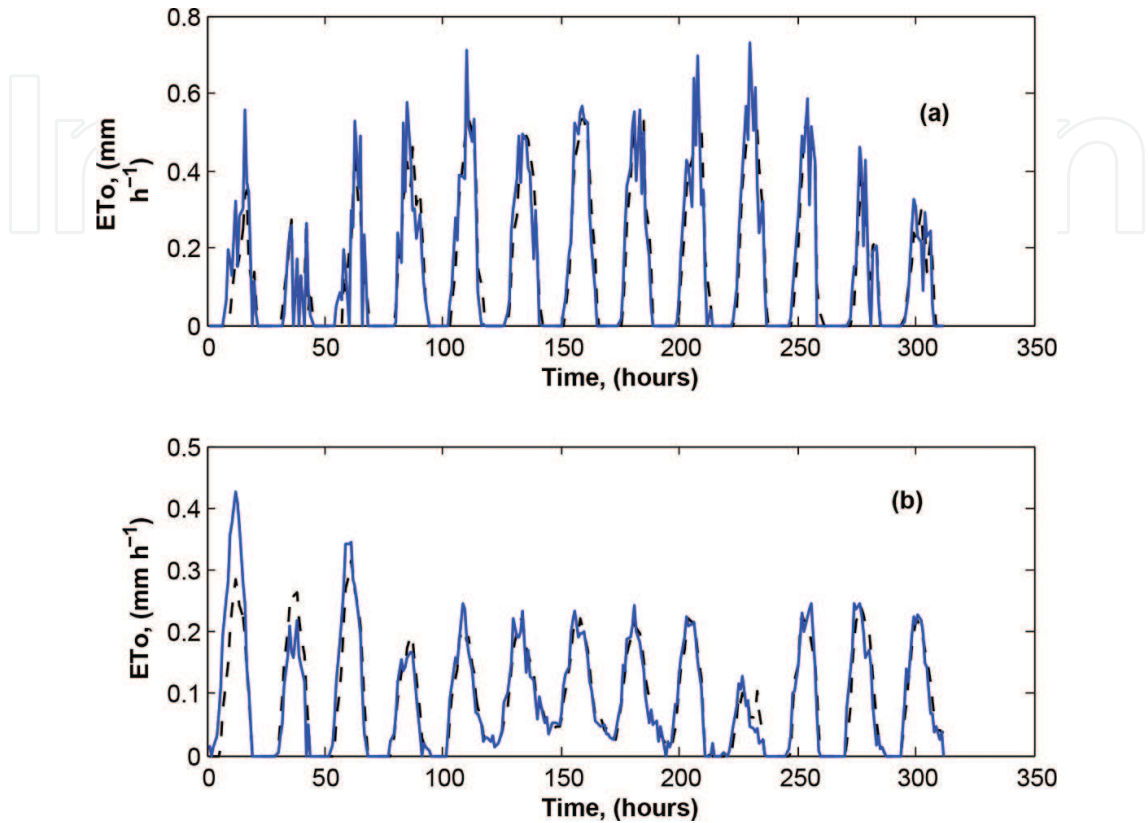
$$\hat{z}_{k+1} = z_k + z_{k-23} - z_{k-24} + b'_1 \hat{a}_{k-23} \quad (5)$$

where  $\hat{z}_{k+1}$  the one-step prediction of the term  $z_{k+1}$ .

Eq. (5) expresses the time series as a linear combination of the previous values and the error term. It shows the relationship between the current  $ET_0$  value, past measurements, and error. This model, which describes the evolution of the hourly reference evapotranspiration in the nursery, must be multiplied by the crop coefficient in order to predict the water needs associated with each plot in the nursery.

For the validation purpose, a comparison between the actual and the forecast  $ET_0$  can be seen in **Figure 1** with data sets of two climatic zones. **Figure 1(a)** corresponds to data of Angers 2005, and **Figure 1(b)** to data of Avignon 1999. The climate in the Angers area is typically oceanic (cool and relatively humid summers), with continental influences (wide temperature ranges). The hardest period for the crops (corresponding to maximum water loss) extended

from July 9th to July 23rd, 2005. The climate in Avignon is Mediterranean, with dry and hot summer temperatures. The period of greatest evapotranspiration demand for the crops extended from August 15th to August 28th, 1999.



**Figure 1.** Temporal distribution of hourly  $ET_0$  during validation. —: Estimated values using PM equation, .....: predicted values from the SARIMA model. (a) Angers July 9th to 23rd, 2005. (b) Avignon, August 15th to 28th, 1999.

One can observe that forecasting errors are most likely within an acceptable range with the average error less than  $0.03 \text{ mm h}^{-1}$ . The forecasting can be considered accurate despite disturbed weather conditions mainly due to quick variations in net radiation. As seen in **Figure 1**, the hourly predictive model provides a good forecast of the reference evapotranspiration for the two climatic conditions.

### 3. Predictive irrigation scheduling

#### 3.1. Preliminaries

We briefly recall the nomenclature related to literature on scheduling in computers and manufacturing systems. Machine scheduling considers in general the assignment of a set resources (machines)  $M = \{M_1, \dots, M_m\}$  to a set of jobs  $J = \{J_1, \dots, J_n\}$ , each of which consists of a set of operations  $J_j = \{O_{j1}, \dots, O_{j\sigma_j}\}$ . The operations  $O_{jk}$  typically may be processed on a single



machine  $M_i$  involving a nonnegative processing time  $t_{jk}$ . Usually, precedence constraints are defined among the operations of a job, reflecting its technical nature of processing. Other important aspects that frequently have to be taken into consideration are release dates and due dates of jobs. A solution to the problem is called schedule, assigns start and end times for the operations with respect to the defined constraints of the problem.

Various optimality criteria are based on the completion times  $C_j$  of the job  $J_j$  in the schedule. The most prominent to mention is the minimization of the maximum completion time (makespan). Another objective can be the minimization of the sum of the completion times. Both measures implicitly attempt to optimize the production costs by minimizing jobs production time. In many situations, due dates  $d_j$  which define a required or preferable time of job completion are available for each job  $J_j$ . It is then possible to estimate the violations due date in terms of tardiness values  $T_j$ . Usual optimality criteria based on this consideration are the minimization of the total tardiness, the minimization of the maximum tardiness, the minimization of the total tardiness or the minimization of the number of tardy jobs.

Scheduling theory covers different models usually specified according to three-field classification  $\alpha/\beta/\gamma$ .  $\alpha$  specifies the machine environment (single-stage systems or multistage systems (covering flow shop, job shop, or open shop problems),  $\beta$  specifies the job characteristics (processing time of job  $j$  on machine  $I$ , or released time, due date or weight, etc.), and  $\gamma$  determines the optimality criterion (makespan, total completion time, total weighted completion time, etc.). These problems appear usually to be NP-hard, and are investigated by approximation algorithms, or heuristics algorithms. The scheduling issue when operations durations are known consists of determining depending of the criterion earlier or latest starting time, earlier latest completion time, and so on.

### 3.2. Scheduling algorithm

Irrigation scheduling has conventionally aimed to achieve an optimum water supply for productivity, with soil water content being maintained close to field capacity. Among the existing irrigation mode trickle, ebb and flow, or sprinkler, the latter is the widely used by growers, and will be considered in the following. The approach remains valuable for other irrigation modes.

A nursery is composed of a set of  $N$  plots in which crops at different stages of growth have different water needs. During early stages of growth, plants water need is relatively low, and increases as the plants canopy extends. Therefore, if precise amounts of water have to be applied, grouping plants within zones of irrigation based on containers size and on stage of growth is important. As plants grow, containers are spaced to allow more sunlight penetration and improve plant quality. Containers spacing and canopy characteristics could affect the amounts of overhead water that fall unintercepted between containers, and should be considered in application efficiency evaluation. Difficulties in water management arise when water availability and equipment are insufficient to permanently meet the full crop water requirement. For example, in operating conditions the respect of both allowable pressure head variation of the hydraulic network and of the sprinkler discharge variation in order to ensure emission uniformity leads to the limitation of the number of plots simultaneous irrigable. The

main line value needs also to be considered since the sum of distributed discharges should be less than the nominal value. Moreover, the management complexity increases during sunny periods with high values of the probability of simultaneous irrigation requirements by the different species. This can sometimes cause considerable irrigation delays. The aim is to develop a satisfactory water distribution plan and to avoid irreversible damage to production. A priority value can be assigned to each plot in order to preserve the most sensitive crops from water stress in comparison with more resistant crops.

When considering a multiple crops nursery with high-frequency irrigation demand under limited resources, irrigation-triggering scheduling consists of which plot to irrigate, when to irrigate, and the irrigation duration, taking operating constraints, cumulative constraints, and temporal constraints into account. To suitably fulfill these objectives, one should minimize the irrigation starting time, the head pressure losses, and the water stress periods. Referring to the preliminaries above, the problem under consideration differs from the standard parallel-machines-sequencing problem because of its multiobjective aspects and because of the fact that operations and jobs are merged. Thus, instead of using the three-field classification  $\alpha/\beta/\gamma$ , the problem is formulated in the following compact form:

$$[r_{c,k+1}^{S^*}, d_{c,k+1}^{S^*}] = \arg \min_{c \in U_{ad}} H(SL_{c,k}^S, WD_{c,k+1}^S, A e_{c,k}^S, p_{c,k}^S, Q_k, D_k) \quad (6)$$

the superscript  $s$  stands for growth stage, subscript  $c$  for plot or crop, and  $k$  for the discrete time.

$r_{c,k}^{S^*}$  is the irrigation starting time,  $d_{c,k}^{S^*}$  the irrigation duration,  $SL_{c,k}^S$  the water stress level of a crop,  $p_{c,k}^S$  the priority of a crop,  $A e_{c,k}^S$  the application efficiency,  $Q_k$  the set of parameters relative to hydraulic constraints,  $D_k$  to the scheduling horizon, and  $WD_{c,k}^S$  to the substrate water deficit.

A simplified hourly soil water balance equation was used to calculate the water deficit. The balance equation was defined as

$$WD_{c,k+1}^S = WD_{c,k}^S + ET_{c,k}^S - I_{c,k}^S + R_k \quad (7)$$

where  $WD_{c,k}^S$  (mm) is the soil water deficit at time step  $k$ ,  $R_k$  (mm) is the effective rainfall,  $I_{c,k}^S$  (mm) is the effective irrigation, and  $ET_{c,k}^S$  is the crop-specific evapotranspiration: ( $\widehat{ET}_{c,k+1}^S$  for the predictive scheduling and  $ET_{c,k}^S$  for the nonpredictive scheduling). The pseudo code of the proposed heuristic based on dispatching rules [29] that prioritize irrigation requests that are waiting for processing is given below:

```

begin
  for k=0 to 23 do
    Compute or forecast ETo
    for c=1 to N do
      Estimate the water deficit
      while k' < Kmax do
        Compute Uad the set of admissible plots
  
```

```

for l=1 to N do
    Build the irrigation sequence
    Update the slack scheduling horizon
    Update plots priority and water deficit
endfor
endwhile
endfor
endfor
end.

```

An irrigation request is emitted when the predicted value or the estimated value of the water deficit exceeds the predefined water stress threshold. As the optimization criteria are often conflicting, not a single but a set of solutions are regarded. The resolution of the problem lies in a hierarchical analysis in which subsets of local solutions are derived from the progressive consideration of the constraints. Roughly speaking, the heuristic proceeds by sequential evaluation of the subsets of solutions. The heuristic performs a soil water balance on hourly basis. It calculates or predicts crop ET and then estimates or predicts actual soil water depletion within the root zone. From the priority rules, predicted irrigation dates and amounts are determined based on the current soil water status and anticipated future depletions.

### 3.3. Simulation results

In order to illustrate the usefulness of the approach based on the predictive scheduling and of the nonpredictive scheduling, a small nursery with 16 plots numbered A1, A2, A3, A4..., D1, D2, D3, D4, was considered, with one crop variety per plot. Plot priority was an integer chosen between 1 and 4, depending on sensitivity of the crop to water stress. The water deficit thresholds were set between 1 and 3.5 mm, while the crop coefficients were chosen ranging from 0.35 to 1. The irrigation water reached the plots through a hierarchical network of main canal, secondary and tertiary canals. The pipeline diameters were fitted in decreasing order of 120 mm for the main, 60 mm for the submain and 45 mm for the sub-submain from the hydrant to the entrance of the plot. The water flow of the main line was fixed at 9 l/s. In order to avert water hammer, water velocity ranged from 0.5 to 2 m/s. From the pressure drop abacus, the maximum water flow per plot was fixed at 2.08 l/s. Considering these hydraulic constraints, only four plots could be simultaneously watered. Application efficiencies ranged from 35 to 80%, depending on canopy development and containers layout on the plots. The software used for the control of irrigation scheduling was written using the Matlab package.

**Figure 2** represents results of irrigation scheduling on day 10, with data of the period, July 9th to 30th, 2013, in Angers. The Gantt chart shows only irrigation events between 10 and 19 h. For the nonpredictive scheduling irrigation events arising after 20 h are omitted in order to relieve the representation. For the same reason, irrigation request times or release times are not indicated.

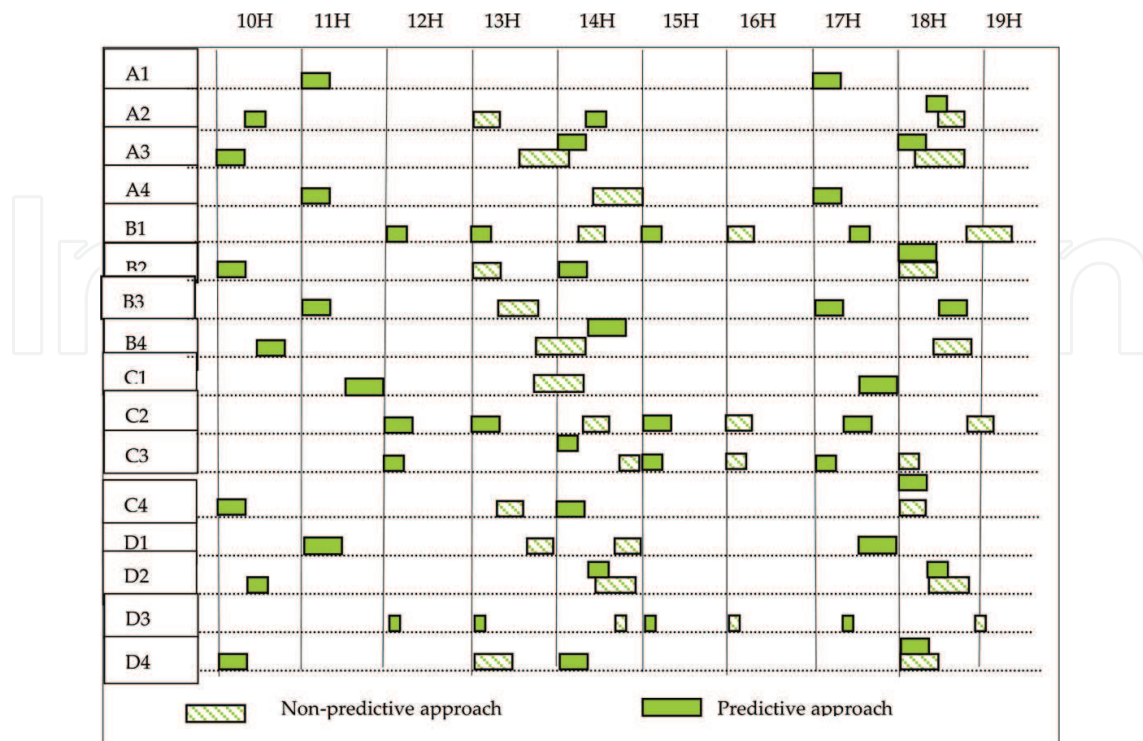


Figure 2. Irrigation scheduling (day 10, Angers, 2013).

One can observe that the irrigation events in the predictive-scheduling approach are more mostly staggered over the working window than those of the nonpredictive scheduling. Indeed, as explained in heuristic description, irrigation requests in the predictive approach are emitted earlier compared to the nonpredictive case. As a consequence, when constraints are satisfied crops are watered before the water-deficit threshold is reached. In this case, crops remain most of the time in a hydric comfort zone. Moreover, doses are reduced leading to a better water sharing or distribution. Irrigation requests are also usually satisfied because of the lower value of the hydraulic network load on the scheduling horizon, and the use of the rules prioritizing the requests. For this simulation, there is no significant bottleneck. A peak water requirements period appears at hour 17. Irrigation events are spread over the scheduling horizon without calling into question the capacity of the hydraulic network. The approach can be considered as sustainable since the amount of water required by the crop is applied at the proper timing to prevent the soil water content from becoming dryer than the management allowable depletion.

In the nonpredictive case, two bottlenecks can be observed as a consequence of sudden high evaporative demands. For the first period 12–14 h, irrigation requests are emitted simultaneously and the algorithm produces the given schedule. There is no idle time. One could deduce that the hydraulic network is well designed, since the irrigation requests dates are not represented. As the demand is greater than the main line, priority is given to the plots satisfying the imposed constraints. For example, between hours 13 and 14, request of plot A1 with weak

priority value is postponed to the next scheduling horizon. A similar behavior is observed with plots A1 and C2 between hours 19 and 20. Between hours 12 and 13, the irrigation on the plots B4 and C1 spans on two consecutive periods, without preemption due to their highest priority value compared to that of A4, B1, and D1. The second bottleneck period 18–20h presents some similarities with the first period. Many irrigation events are delayed compared to the cases of predictive scheduling. The major drawback of this approach is that the decision to irrigate is made after the plant has suffered some amount of water stress.

In general, one can observe that the recovery of crop water status is rapid and water status is significantly better in the predictive scheduling than in the nonpredictive scheduling.

## 4. Conclusion

In this study, we proposed a predictive approach of irrigation scheduling in nurseries, with the objectives of minimizing the water stress periods of the crops while optimizing the use of disposal materials. The time-series theory enabled to obtain good forecast of the potential evapotranspiration allowing the prediction of crops evapotranspiration. A heuristic of irrigation sequencing was developed and was applied on a small nursery designed for the purpose. Simulation results with predictive and nonpredictive scheduling showed the ability of the predictive-scheduling approach to proper timing the amount of water required by crops in order to prevent water stress periods which may adversely affect the crop yield. Extension of the approach to sudden changes in weather conditions is under study in order to improve the prediction capability of the heuristic.

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