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Hydroponics water management using adaptive scheduling with an on-line optimiser

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Abstract

An optimisation-based methodology for irrigation control and nutrient supply is developed using common measurements of greenhouse climate. The process measurement has a long time delay, and a feedforward (FF) control loop based on a model-based estimate of water losses is used. A long feedback loop, by which the FF model is adapted using output error feedback, is the mechanism used to minimise the control error. To read the output error, a drain measuring device, or soil moisture meter, is necessary. The optimisation method used is a general tool developed for real-time application and is capable of optimising linear and non-linear systems. The minimisation algorithm used is based on a variant of the Powell direction set method in multiple dimensions. It compares favourably in speed of convergence and accuracy when compared with linear regressors for linear systems. It is therefore used as a generalised tool embedded in a modern greenhouse management system. The method allows on-site on-line identification of plant water needs. As an added benefit, the method provides information for the creation of crop transpiration models.

Keywords: Irrigation; Optimisation; Models; Intelligent control

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1. Introduction

Contemporary greenhouse operations require precise control of irrigation and nutrient supply in order to optimise crop growth and minimise cost and pollution due to effluents. Moreover, in Mediterranean countries and elsewhere, there is a need to minimise water waste due to seasonal shortages. In modern greenhouses, nutrient supply is computer controlled and based on measuring salinity and compensating deficiencies using a mix of clean water and two or more stock nutrient solutions. The process of applying this solution to the crop presents several control problems such as time delays and seasonal variations due to plant growth. The monitoring of the process may have a minimal time delay, as in water content measurement in soil or substrates, or an extremely long time delay, as in drain flow measurement. Several solutions to the nutrient supply problem have been proposed such as direct feedback control of drain water flow in both closed and open growing systems using flow measurement of the drain water. Gieling et al. (2000) presents a design for a water supply controller using system identification but the proposed controller performs well only when a feedforward element is added in the control loop, in order to estimate water uptake as a function of global radiation. On the other hand, progress has been achieved in model prediction of crop irrigation needs. Usually, a transpiration model (Stanghellini, 1987) is used that predicts plant transpiration based on ambient conditions of temperature, solar radiation, CO_2 concentration and vapour saturation deficit. Approaches based on such experimental models lead to open loop control of water and nutrient supply, using model estimation of crop needs (Hamer, 1997). These growth-based models, whether complex multivariable non-linear systems or reduced order models, usually suffer from an inaccurate estimate of the transpiring surface (leaf area index), when used without an error correction scheme.

This work proposes a hybrid approach, where a simplified crop transpiration model is used to predict the necessary supply of water. At the same time, drain water flow from the crop is measured using an appropriate flow sensor. Using the error between drain measurement and the model estimate, the coefficients of the model are adapted iteratively. The adaptation process is continuous so that the model accounts for temporal variation of load (i.e. radiation) while it is also adapted for seasonal variations of crop growth.

Control systems capable of operating over a wide range are usually designed by combining feedforward (FFC) and feedback (FBC) control loops to provide good performance and disturbance rejection. With a good adaptive FFC, the system is inherently stable and is rapidly brought to the vicinity of the desired operating trajectory, and only incremental actions are left to the FBC (Fig. 1). In such structures, the FFC must provide good nominal performance. A non-linear programming technique is used to optimise the dynamic performance of the system, based on a selected performance index. The FBC must be designed to offer robust performance and stability, and may be implemented using separate classical Single Input Single Output (SISO) controllers (lead-lag or Proportional plus Integral plus Differential (PIDs)). In feedback systems, when the system dead time becomes a

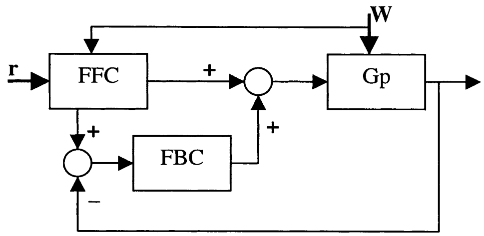

Fig. 1. FF/FBC structure for robust wide range control for processes with uncertainties and long time delay. R, goal; w, disturbance.

significant portion of the total time constant, a feedforward component becomes necessary. A Smith predictor (Sigrimis et al., 1999) can implement the FF actions for moderate dead time:time constant ratios. When this ratio is very large, the feedforward component contributes most to loop performance and the feedback component may become unnecessary.

The iterative adaptation process of the crop transpiration model and irrigation process controller is shown in Fig. 2. The adaptation process provides robust systems with improved performance. New understanding of the complexity of natural systems has been achieved recently in research on complex adaptive systems. Reduction of complex phenomena at a higher level to simpler problems at a lower level (Wildberger, 1997) is used. Systems in this new field of study share a common characteristic: adaptability. A complex system is considered to emerge from the interaction of multiple, autonomous, intelligent agents, competing and co-operating in the context of the overall system environment. In this view, autonomous intelligent agents can control a complex greenhouse system, one for each temperature (Goggos and King, 2000), CO_2, light, humidity and root environment control. These agents can utilise any well-known decision support methodology (maximum likelihood, fuzzy expert, etc.) and are best suited for the decision level control (optimised trajectory path, conflict resolution, control system configu-

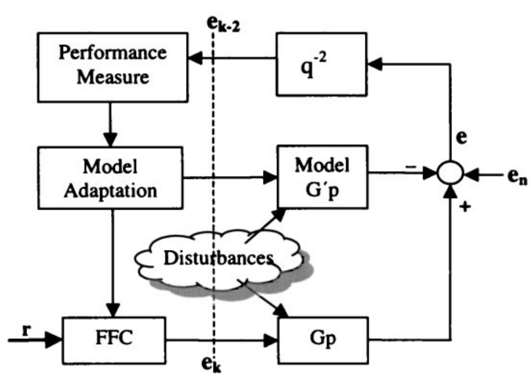

Fig. 2. General structure of the adaptation process of the crop transpiration model.

ration, etc.). Their autonomous nature promises to build co-operative systems of high maintainability, i.e. agent upgrade, or a new agent addition, as we learn more about the controlled plant. Other adaptive systems developed recently (Ferentinos, 1999) manage to accurately model the root environment of hydroponic systems and give useful predictions of major variables of this environment, using neural networks. These predictions can be used for further improvement and intelligent adaptation of the irrigation control process.

All these systems are more flexible in providing higher level management strategies, as they use multiple criteria for adjusting the performance index to include constraints reflecting financial or environmental issues. The system described provides the core for expanding to a multi-agent managerial system in the near future.

2. Materials and methods

2.1. Model building

In irrigation systems, the objective is to supply water at a rate V_o to cover the plant water needs $(1-f)V_o$ while ensuring a certain bleed (fV_o) on the system. This bleed is necessary to 'clear out the contamination' and to maintain favourable conditions in the root environment. The percentage f depends upon the purity of the water source and on the contamination rate, which may depend on the temperature of the root environment and other factors. In this regard, f could be set as a function (i.e. a virtual variable in MACQU ; Rerras et al., 1998) that can vary with weather conditions for a better tuning of irrigation and additional savings in water, nutrients and environment. This principle is general and found in all irrigation types, i.e. Nutrient Film Technology (NFT) damping rate, continuous bleed or damping of closed irrigation substrate systems with recycle, open irrigation systems with drain rate. The latter is a common greenhouse-growing practice and the irrigation water is supplied in specified time cycles. In each cycle, the amount of water supplied, V_o, is determined by the grower in order to satisfy crop requirements. This simply represents a non-adaptive FF model estimate implicitly used by the grower, usually to set a fixed scheduler. The approach taken is to ensure that the growing medium saturates from the presence of an amount of drain water. The drain is typically set at around 10–20% of the irrigation amount (V_o) required to secure desired nutrients concentration in the root environment without excessive loss on waste water and fertiliser. Defining the fraction of drain water as f, the real crop evapotranspiration as E^* and its integral as SE*, the current growing practice can be expressed by:

$$\mathrm{SE}^*\big|_{T^*} = \int_t^{t+T^*} E^*\,\mathrm{d}t = (1-f)V_o \tag{1}$$

This reality is depicted in Fig. 3 for the process I to II. Assume that the model relating crop transpiration to climate conditions is of the form:

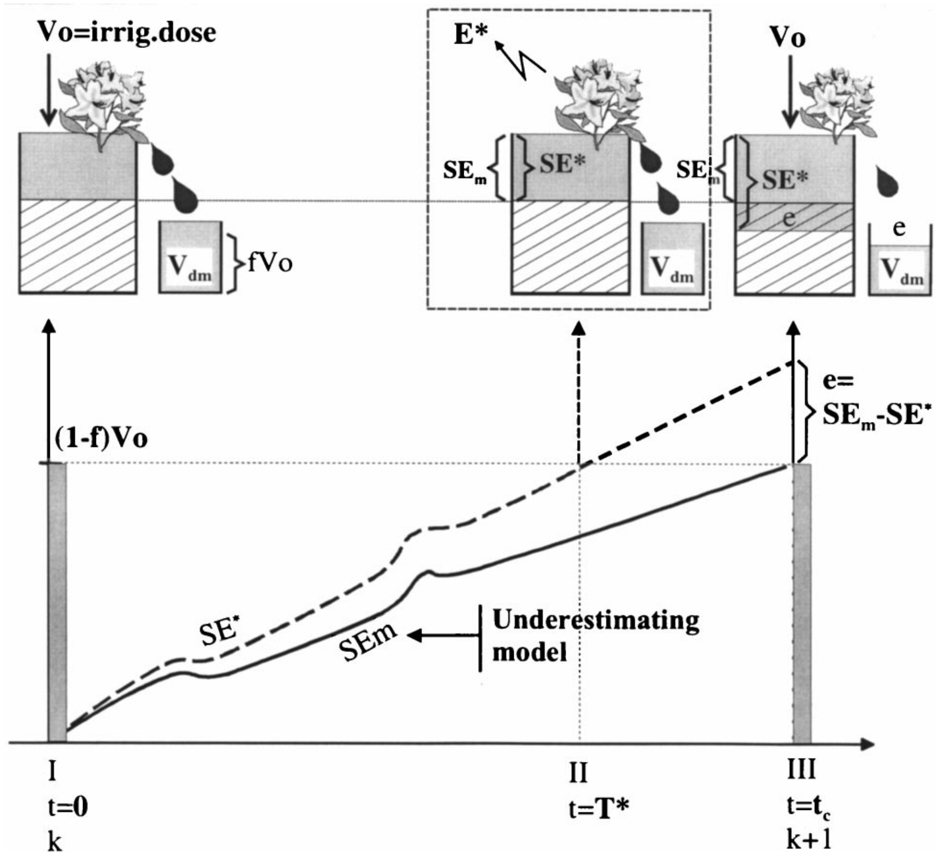

Fig. 3. The concept of model prediction of irrigation needs and its error appearance in measured drain.

$$E_m = \alpha\ S + \beta\ \text{VPD}_a + \gamma \tag{2}$$

Crop transpiration E_m (kg/m^2/s) is related to solar radiation S (W/m^2) and air vapour pressure deficit VPD$_a$ (kPa) through suitable coefficients (α, β, γ) (Monteith and Unsworth, 1990). Then, the crop transpiration accumulate SE$_m$ can be computed by integrating this model for the duration of the irrigation cycle, t_c. In the general case, the model of Eq. (2) has unknown parameters that depend on factors such as crop, growth stage, leaf area index (LAI), leaf resistance, etc. In the presented model, the parameter α represents the percentage of intercepted energy and relates to LAI, β represents leaf transpiration resistance and γ accommodates any other systematic factor.

However, if a measurement of the drain water is available then the true crop transpiration can be determined by integrating drain water rate and using Eq. (3).

$$\text{SE}^* = V_o - V_{dm} \tag{3}$$

where V_{dm} is the drain water accumulate that, according to Eq. (1), with an accurate model should be equal to fV_0 (Fig. 3). In fact, this measurement is used in feedback control of irrigation in closed systems (Gieling et al., 2000). This form of control requires careful design due to the time delays present in the irrigation process. Also, due to system drifts, the controller design should incorporate robustness. This is shown in Fig. 4 where the drain water rate measured during irrigation cycle $k+1$ is accumulated at the onset of the next irrigation cycle $k+2$ to estimate the accuracy of the model during cycle k, from time t_k to t_{k+1}. This time delay can be from minutes to hours and depends on the length of the irrigated line and the characteristics of the substrate. With such a posteriori measurements, post-detection and post-processing is the only way to use feedback information, through the use of model adaptation in a model-driven approach.

The alternative proposed here is to utilise this measurement in order to determine the unknown parameters of Eq. (2). Then, with well-tuned parameters, the irrigation process could be controlled in a feedforward loop. Moreover, if the parameters of Eq. (2) are continuously estimated, then the system can compensate process drift by model adaptation. Parameter tuning can be accomplished using a minimisation algorithm if an appropriate performance function is chosen. In this case, the performance criterion to minimise is simple to create. During the irrigation cycle, the integral of Eq. (2) is monitored so that the estimated evapotranspiration ($\mathrm{SE_m}$) is available at any instant:

$$\mathrm{SE_m}\big|_{t_c} = \sum_{0}^{t_c} (\alpha S + \beta VPD_a + \gamma)\Delta t \leq (1-f)V_o \tag{4}$$

When the summation in Eq. (4) reaches the equality condition on the right, the cycle is terminated and a new irrigation cycle is triggered.

2.2. Model adaptation

As depicted in Fig. 3, if for example Eq. (4) underestimates the transpiration, this will lead to a longer irrigation cycle, i.e. delayed application of the irrigation water dose V_o. The real transpiration will be higher than estimated and, as a result, more water is retained in the substrate and less drain water will be measured. The

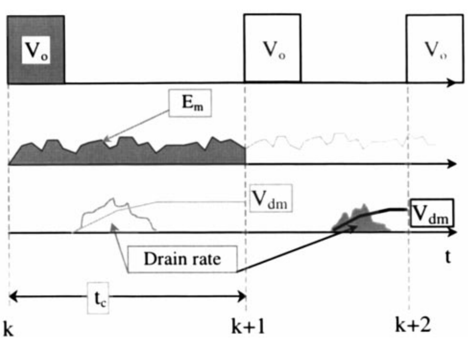

Fig. 4. Depiction of irrigation dose (V_o), momentary plant transpiration (E_m), measured drain water rate and accumulated (V_{dm}), in a typical irrigation cycle.

measured error e_m in the expected drain is actually the error of transpiration model estimate, including any additive noise sources. Using Eqs. (3) and (4), we derive:

$$e_m = SE^* - SE_m + e_n = (V_o - SE_m) - (V_o - SE^*) + e_n = fV_o - V_{dm} + e_n \quad (5)$$

This is simply stated as:

$$e_m = (\text{model expected drain}) - (\text{measured drain}) + (\text{random noise})$$

In a form suitable for the optimisation algorithm, the percentage relative error of the kth irrigation cycle is:

$$e_k = 100(fV_o - V_{dm})/fV_o \quad (6)$$

The performance criterion J is defined as the sum of errors squared of the last N irrigation cycles, i.e.

$$J = \sum_{k-N}^{k} e_i^2 \quad (7)$$

The number N of irrigation cycles in the performance measure is chosen by the user and factors considered are: model stability, probable noise sources in the drain collecting duct, growing speed of the crop, noise sources in the plant level intercepted energy estimates, etc. Further discussion and analysis will appear in a forthcoming paper together with results on using the model adaptation process for diagnostic purposes. Using the fact that a linear model was used (Eq. (2)) and the assumption of noise-free measurements, one could simply apply a linear system of equations involving only the last three irrigation cycles to solve for the three unknown parameters. This assumption can be used to get a good initial estimate of the parameters. Moreover, the performance measure chosen by Eq. (7) also suggests that a simple linear regressor could apply, either by successive batch calculations or using an appropriate recursive algorithm (Sigrimis and Rerras, 1996). Given the fact that, in MACQU , a Generalized Optimiser (GO) is embedded, a comparative study is included in the Section 3 to test the GO for accuracy and speed of convergence.

The algorithm that accomplishes the task of tuning the parameters and controlling irrigation can now be stated (Table 1). In Table 1, the unshaded lines represent the regular coded irrigation algorithm without adaptation, while the shaded lines represent macros executed automatically when the optimization process is enabled (Table 2).

The proposed method is based on common measurements of ambient dry-bulb temperature, relative humidity and crop level solar radiation, which are used as a means for controlling the greenhouse environment. The first two measurements are converted to VPD using a virtual function from MACQU controller math library. The method additionally requires a flow sensor (such as a tipping bucket or tipping spoon, etc.) on the drainage of the irrigation channel.

The estimate of the model parameters proceeds with each irrigation cycle. The estimation is iterative and is based on the availability of irrigation drain flow measurement. If drain water does not appear at all then there is no estimate of

Table 1
Automatic Optimisation Algorithm (AOA) for irrigation

1.	Setup a virtual function for P.M.: $J = f(N)$
2.	Setup Optimizer X
3.	Define V_o, f
4.	Apply V_o, $k = k+1$, $t_c = 0$
5.	Do Loop
	Calculate SE_m (from Eq. (4)), clock t_c
	Measure drain and integrate V_{dm}
	While $SE_m < (1-f)V_o$
6.	Compute SE* (from Eq. (3)) and e_k (from Eq. (6))
7.	Compute J
8.	Call OPTIMIZER X to update [α,β,γ] using J
9.	Go To step 4

error and the method must take special steps to recover. Two subsequent irrigation cycles are shown in Fig. 4.

2.3. The optimiser

The optimiser module is an iterative search algorithm that can adjust the model parameters in order to minimise the specified error metric. The algorithm is a variant of the 'Powell direction set method in multiple dimensions' minimisation algorithm (Press et al., 1992). This algorithm does not need any process model or gradient information to conduct the parameter search and can therefore accommodate any user-defined performance criterion. Instead, it explores the parameter space performing line minimisation along the way, always searching for the best (conjugate) directions. In this case, the search for better parameters never stops in order for the algorithm to detect drifts of the system characteristics (i.e. plant growth, etc.) (Fig. 5). In order to achieve a better fit of the search parameters and shorter search times, the parameter space is separated into two regions of environmental conditions as determined by solar radiation (i.e. regions with low or high solar radiation with a boundary at 100 W/m^2). A separate set of parameters (α, β, γ) is created for each of these regions, resulting in the formation of a parameter dictionary. Each time the environmental conditions shift to a different region, the

Table 2
Operator steps to set-up the AOA of Table 1

1.	Specify a virtual variable computing the Performance Measure (P.M.)
2.	Setup generalised optimiser X
	–number of parameters and first estimates I
	–learning rate η
	–safety constraints C
3.	Setup (step 3 of Table 1) Irrigation Program Y, and Start
4.	Assign GO-X to Irrigation program Y, enable GO-X

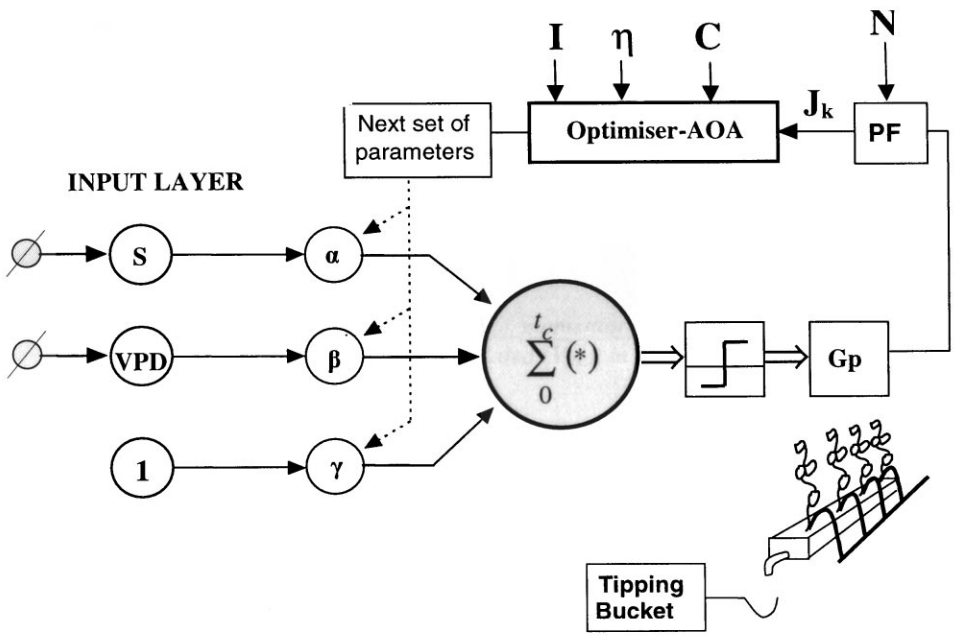

Fig. 5. A simple linear perceptron for learning of the crop transpiration model.

optimiser switches to the appropriate parameter set from the dictionary and continues with a new experiment. This is a simple form of gain scheduling.

This algorithm is embedded for general use in the MACQU greenhouse control software (Rerras et al., 1998; Sigrimis and Rerras, 1995). The MACQU operator must execute only the steps in Table 2, which are commands to the greenhouse controller. Having completed the steps of Table 2, the process automatically generates the algorithm AOA of Table 1 and runs continuously in the controller unattended.

3. Results and discussion

3.1. Simulation

Preliminary results have been produced with simulated transpiration data on a plant linear model, which was explicit on solar radiation, relative humidity and temperature, instead of radiation and VPD. This simulated learning used an enhanced variation of the Hooke–Jeeves (Shoup, 1979) algorithm (Rerras et al., 1998). This algorithm explores the parameter space by modifying one parameter at a time while searching for a gradient. After all parameters have been explored, the algorithm moves in the direction of steepest descent until no further progress is attained. Thus, the algorithm cycles between exploration and pattern searches until a local minimum is reached. The results can be summarised in the charts of Fig. 6, showing the performance progress with regards to two of the three inputs, the temperature and the radiation. In each chart, the dot-headed grid represents the performance map after a certain number of experiments represented by the number of successive pattern searches. Each pattern search is preceded by a maximum of three explorations. Each exploration demands evaluation of the performance (one irrigation cycle that lasts approximately 1 h).

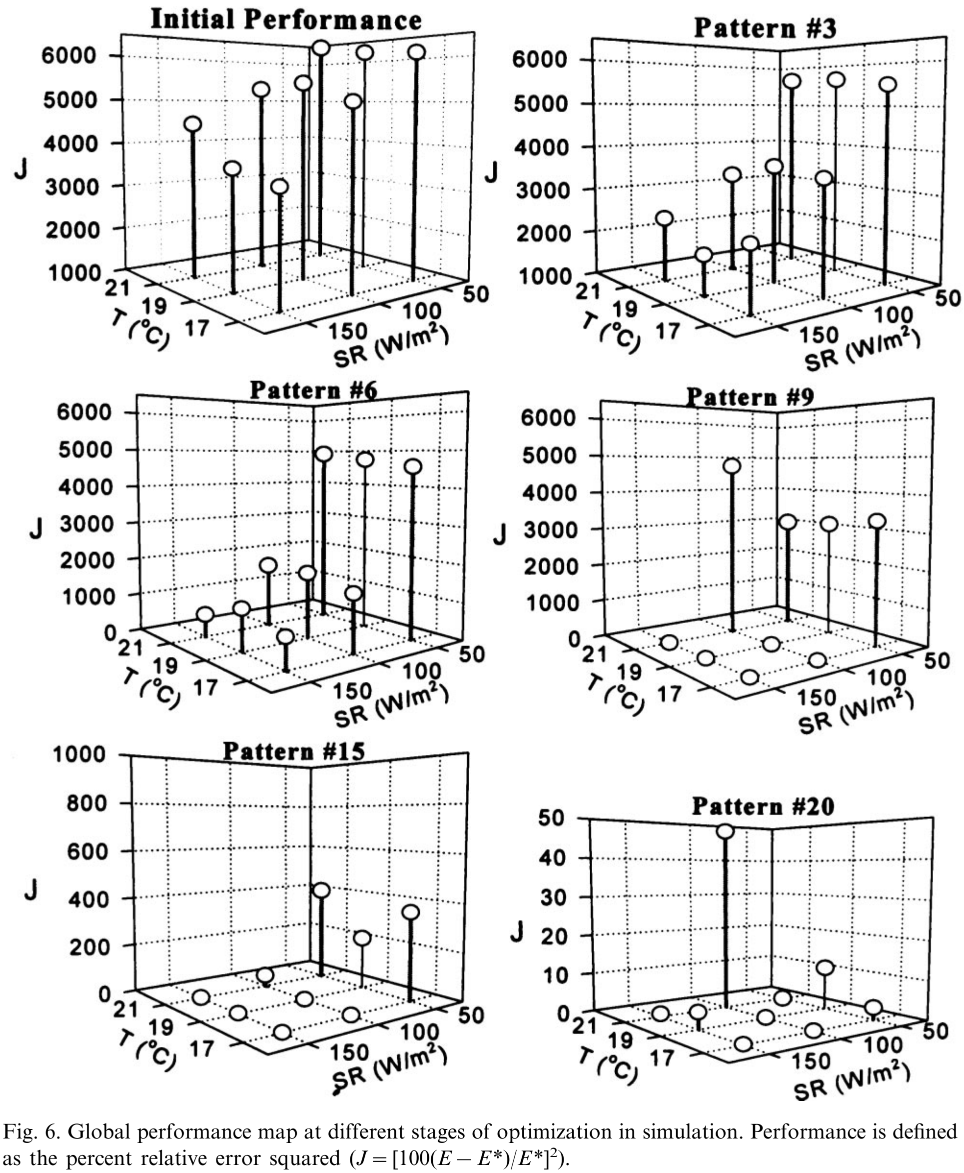

Fig. 6. Global performance map at different stages of optimization in simulation. Performance is defined as the percent relative error squared ($J = [100(E - E^*)/E^*]^2$).

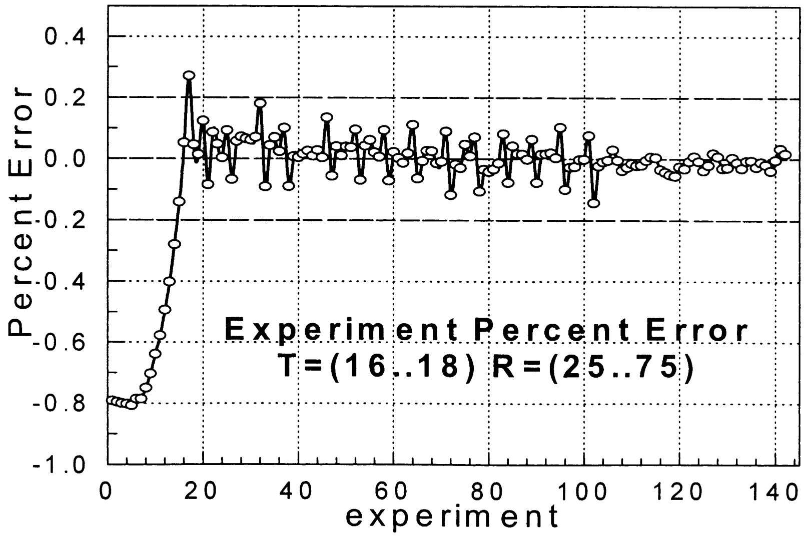

Fig. 7. Estimation error versus experiment number (simulation) for a single set of parameters.

The progress in a single set of parameters is shown in Fig. 7. It can be observed that, after an initial set of pattern searches, the error settles at less than 20% in fewer than 20 evaluations. In this chart, all explorations are shown (regardless of success). It can be observed that the algorithm oscillates within a small range of errors. This oscillation is explained because experiments are not conducted at a specific point, but over a range of conditions (cell temperature, 16–18°C; cell radiation, 25–75 W/m^2). Consequently, the error cannot be constantly reduced because the same 'best' parameters produce somewhat different errors under varying conditions within the cell, in which the real plant is not perfectly linear as assumed by Eq. (4). This is the main reason why a more advanced optimisation algorithm was used in the real experiments instead of the Hooke–Jeeves algorithm. In a real greenhouse environment, the range of conditions is much wider and this algorithm would perform unsatisfactorily. On the other hand, as shown in the following section, the new algorithm proves to be very fast in the wide range of real life conditions.

3.2. Learning experiments

Experiments with the new optimiser were performed in a greenhouse at the Agricultural University of Athens where a rose crop was grown in channels of perlite substrate using an open loop irrigation–hydroponic system. In one of the growth channels, the irrigation was adjusted using the optimisation method. At the end of the channel, the drain water flow was measured using a tipping bucket sensor. The irrigation dose was fixed at 6 l per application and the model was used to determine the irrigation application timing. At the same time the model parameters were tuned using the optimiser. The initial values for the model parameters were assigned using rough estimates of evapotranspiration versus solar radiation and air vapour pressure deficit. Even so the initial algorithm errors were not excessive and, in any case, they were reduced quickly by the process of optimisation.

Fig. 8 shows measured evapotranspiration versus model predictions during 3 days of experiments. Significant reduction of prediction errors can be observed, especially in the third day of experiments where the errors do not exceed 10% at any time. The graph in Fig. 9 shows the accuracy of the irrigation program proposed by the model after 3 days of learning. The set point for the drain was set to 600 ml (10% of the irrigation dose, $V_o = 6000$ ml). During daytime, there was virtually no error in the draining achieved, while early in the morning and late in the night the errors were $+3$ and -1%, respectively. It is worth noting that a big source of noise (e_n) existed during the experimental period shown in Figs. 8 and 9. This was caused by drain water absorption by trash accumulated in the drain duct ahead of the drain meter.

3.3. Comparison with linear regression models

Since the performance criterion in this application is the sum of squared errors, the optimiser-estimated parameters from the model can be directly compared with those derived from linear regression of the same data set. The linear regression estimation used is an a posteriori method, meaning that the data set had to be

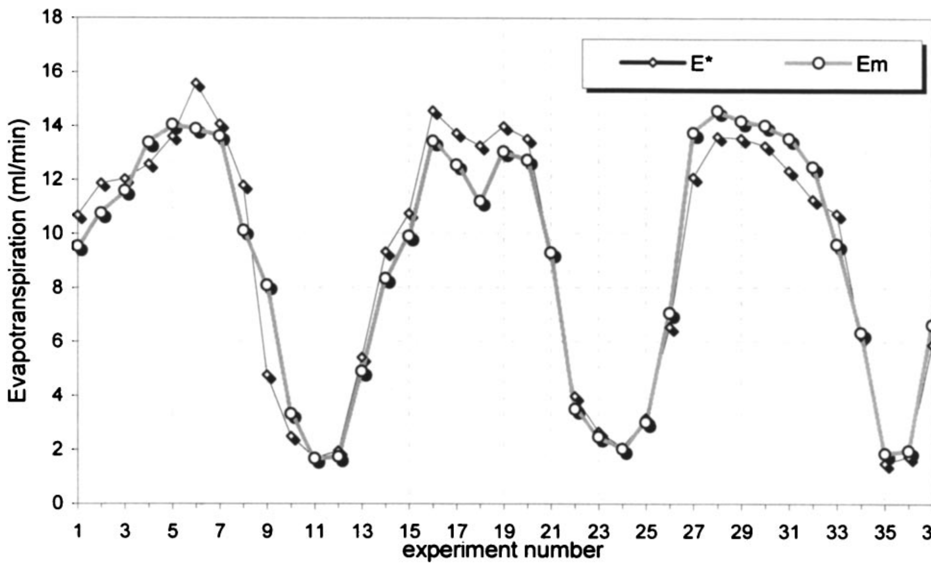

Fig. 8. Measured evapotranspiration (E^*) vesrus one-step ahead model prediction (E_m) during 3 days of learning experiments.

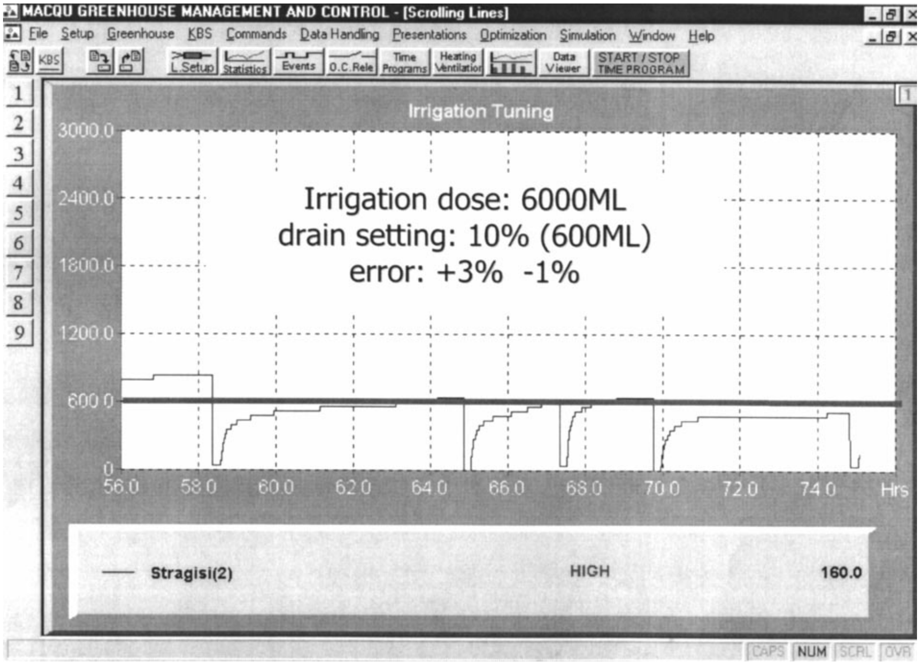

Fig. 9. Irrigation accuracy attained after 3 days of learning, showing cumulated drainage approaching the targeted 600 ml very closely.

collected before estimation of the parameters could be carried out. Otherwise, on-line relative least squares algorithms exist (Sigrimis and Rerras, 1996) in case a linear tool is desired. Nevertheless, the comparison served to show that the parameters estimated by the generalised algorithm are reasonable compared with the standard estimation method since the error criterion is the same in this case (the SSE). Table 3 shows the parameters estimated by the two methods.

The irrigation process was simulated with the linear regressor-estimated parameters and produced exactly the same timing (t_c) for the irrigation of the days used for the learning experiments. This means that, despite the slight difference in parameters estimated by the regressor and the conjugate gradient method, the model of Eq. (4)

Table 3
Comparison of parameters estimated by optimisation and linear regression

	High solar radiation			Low solar radiation		
	α	β	γ	α	β	γ
Generalised optimiser	0.0108	2.246	0.580	0.0224	1.932	−0.279
Linear regressor	0.0117	2.015	1.205	0.0335	1.842	−0.293

has enough redundancy and noise in the data that make the two sets shown in Table 3 equivalent. For example, the linear regressor tends to estimate lower β and higher α values without affecting the end result. This means that the variable associated with β (the VPD) has a large covariant part with that of α (the radiation S). This is true from the physics of the process as VPD controls the latent heat flux, which represents the major part of the intercepted radiant energy. Many researchers use one variable only (Gates et al., 1998; Hamer, 1997) to approximate the process of transpiration.

3.4. Potential for fault detection

A sudden large error in expected drain or a sharp change in the model parameters can be attributed to faults in the hydro-mechanical gear (faulty V_o, γ) or the plant canopy and physiology itself (change of α, β). Such events can be used to feed a fault detection algorithm. This was inspired by an event after the 3-day period of learning experiments. Mechanical damage caused water shortage, water stress and subsequent partial defoliation. The consequence after repair was as a sharp decline of the α and β parameter estimates, and the system was able to adapt to this system drift with 1 day lag. The fuzzy KBS system native to MACQU has a subset of diagnostic rules to provide user feedback with comments on the status of the crop. Several rules were added after the event on the sum of α and β. We are presently attempting to relate the drift of the α/β ratio to more detailed physiological functions. This technique can contribute to a better understanding of plant responses and may be an important component necessary to implement the Speaking Plant (Hashimoto, 1989) monitoring system of the future.

4. Conclusions

The preliminary tests of the irrigation control method show that it is a good alternative to the currently available techniques used for irrigation and nutrient supply control. Irrigation tuning is achieved in a purely feedforward loop. Instability problems due to the delay in the feedback loop are avoided since feedback is used only for tuning the model parameters. Compared with robust control designs, the proposed technique requires virtually no effort for its application on a specific site. Thus, the problem of controlling the water supply is solved in a very straightforward manner.

The current practice on perlite or pumice and other natural substrates is mostly using the grower's estimation capabilities and the 24 h total drain measurement, to adjust the daily fixed-time irrigation schedule. The method of model adaptation based on a drain-measuring device provides high accuracy and, more importantly, 'weather following'. Compared with model-based control techniques, it offers the ability of on-site on-line tuning that removes the need for exact knowledge of a plant transpiration model. Another significant advantage over advanced control techniques is its simplicity and transparency to the user. Thus, the method achieves the same accuracy with other methods that directly monitor the water level, i.e. in rock-wool substrates. Furthermore, it provides higher safety as the measurement of the drain reflects to a large sample or even the total population of plants instead a single plant measurement.

Splitting the day in two or more regions involving different levels of the prime factor of evaporation, which is the radiant energy, proves to be useful for many reasons. The experimental runs for separate high and low radiation have given model parameters that are extremely accurate for the low radiation regime and especially for the night hours. Under low process noise conditions, high accuracy can be achieved in all operating regimes. A sudden large error in expected drain or a sharp change in the model parameters can be attributed to faults in the hydro-mechanical gear or the plant physiology itself and run fault diagnosis.

Currently, the development is applied on commercial production sites to evaluate growers' responses and operational data from different crops.

Acknowledgements

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