Computer Integrated Management and Intelligent Control of Greenhouses

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Greenhouses are complex systems with many variants and many different user requirements. Modern technologies are cost effective and very powerful to meeting diverse user control and management requirements. Optimization tools are making analytical and expert methods practically applicable. The system described features generalized functions for process control, configurable to meet greenhouse control requirements. Intelligence is shared among low level control loops in the controller and high level decisions made at the central process computer. An open Knowledge Based System, in the form of tasks and subtasks, provides an elegant way of rapid program development. Fuzzy decisions and fuzzy controllers at the supervisory level can provide adaptive reference (set-point) generators, which are key elements for near-optimal greenhouse control. The system is also equipped with an on-line process optimization tool, which was built based on a modified search algorithm with accelerated learning. Each process when entered under the optimizing monitor, is performance driven, conducts real experiments on the site and uses a modified descent method to maximize performance. An adaptive system guides the selection of control parameter values on-line, in a process searching for the global minimum of the cost function. This paper presents the general features of the system, how it can be set-up to achieve specific goals and presents results of tests conducted for low, medium and high level control and supervision.

Keywords : intelligence, knowledge based systems, optimization, process control

INTRODUCTION

Agricultural systems, including the well-structured and studied greenhouse operations, exhibit large variability and can only be represented by complex models. Large dimensions usually create problems in climate uniformity and we rely on, good and sufficient design, and effective distribution, of sensors and actuators for achieving the desired performance. Even the most common problem of sensor location can lead to large deviations in operational characteristics.

Unstructured uncertainties of models need a robust adaptive scheme, such as identification and switching among locally linearized models. An improvement of the method of switching piecewise linearized models of nonlinear systems has appeared recently in the control literature. This method uses fuzzy rules to combine clustered linear models (Takagi–Sugeno models) of the system to make possible the analysis of stability robustness of nonlinear systems.

Control systems for wide-range operations are usually designed by combining feedforward

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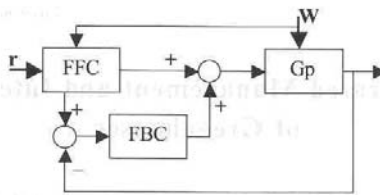
Fig. 1 FF/FBC structure for robust wide range control for processes with uncertainties and long time delay.

(FF) and feedback (FB) control loops to provide good performance and disturbance compensation. With a good adaptive FF control the system is inherently stable and is instantly brought close to the desired operating trajectory, and only a smaller range of actions is left for the FB control (Fig. 1). In such structures (FF/FB), the FF control must provide good nominal performance, and a nonlinear programming technique is used to optimize the dynamic performance of the system, based on a selected performance index. The FB control must be designed to offer robust performance and stability and may be implemented using separate classical SISO controllers (lead-lag or PIDs). The modern H^∞ technique for multi-input, multi-output (MIMO) systems has been used by other authors (Weng and Ray, 1997; Arvanitis et al., 2000).

Researchers report an overwhelming satisfaction in implementing pioneer expert systems for the energy and general management of greenhouses or other agricultural processes. Nevertheless, the number of actual implementations of such systems in real practice remains small compared to the number of systems successfully demonstrated in prototype form. This discrepancy suggests that there are concerns about the cost and difficulty of incorporating expert systems into an Integrated Greenhouse Management System (GMS).

Part of this effort was to determine why integrating an expert system or other artificial intelligence (AI) applications in a GMS is more complex than adding a conventional application. Based on such an analysis the interfaces needed to achieve an effective integration were defined. This groundwork led to the development of a software environment, designated as MACQU (MAnagement and Control for QUality), which hosts a native expert shell, *open* for developing applications and supporting the necessary interfaces to the GMS. The developed environment can support genuine management functions, and interfaces seamlessly with a fuzzy logic development mechanism, which can support, intelligent alarm processing, fault detection and diagnosis, and high-level management decisions.

Protected cultivation is leading to a broader interface between engineering, physiology and biology. The effects of environmental factors on production quality and productivity are fundamental elements to be considered in determining the climate management strategy. The objectives of the MACQU system was to:

1. Reduce the amount of water and nutrient chemicals and enhance transpiration (Jolliet and Bailey, 1995; Gieling, 1997).
2. Improve the quality and optimize energy consumption (Stanghellini, 1987; Garcia et al., 1996).
3. Develop a modern hardware and software system to integrate the gained knowledge into the management and control of crop production (Sigrimis and Rerras, 1996).

The greenhouse (GH) production process must be viewed and managed at different time scales. Within MACQU the overall process is organized as depicted in Fig. 2. This scheme provides a platform for an open system to implement all modern control techniques and plant
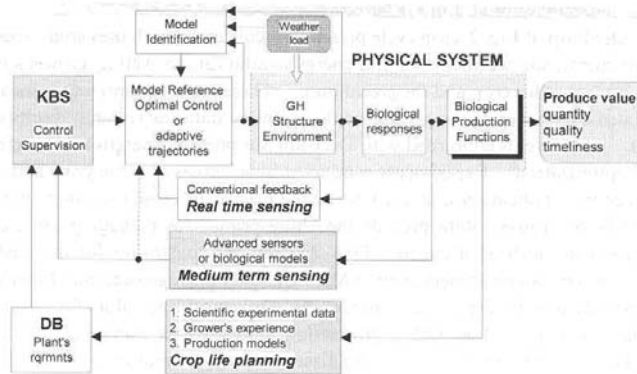
Fig. 2 Multiscale management and control of greenhouses.
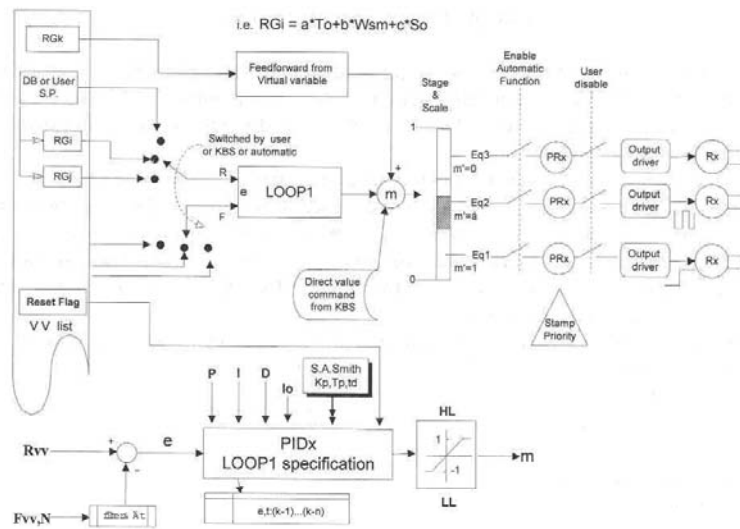

i.e. $RGi = a*To+b*Wsm+c*So$

Fig. 3 Building of a closed loop control mechanism.

management strategies. At the inner loop of Fig. 2, GH physics, disturbance loads, coupled targeted variables, plants' macro-environment as well as equipment variants, with their mode of operation and control methods (ON/OFF, PDM, disturbance compensated PID, FF/FB control, etc.) are met by using virtual variables and control loops (see Fig. 3).

At the medium term of sensing and reacting loop (Fig. 2), micro-environmental issues, plant's biological responses (water/heat/cold stresses, time gradients and risky conditions, etc.) and stage of growth are taken into account. MACQU has considered the possibility of connecting advanced sensors for the real practice. At this stage this concept is only met by expert models (virtual variables can create models i.e. TIVs, other integrals of biological significance, etc.). This loop responds to processes in the time scale of hours to weeks and are

the means to generate optimal diurnal set-point trajectories.

At the outer loop of Fig. 2, crop cycle planning is concerned with user goals, specific plant variety requirements, site weather data and energy availability as well as grower's experience for the management of his crop and the greenhouse. These are long-term responses and regard the accumulated experience of the grower or the scientific data (as research results or growth models, etc.). This level is concerned with Decision Support for operations management and expert mode optimization. Experiments conducted by scientists over the years and concluded results enhance the application domain knowledge needed to close this long-term feedback loop. Scientific or grower's data provide the "blue prints" for managing the greenhouses. These data are better utilized if fed to a DSS that sets the constraints for the medium term loops. This concept can be implemented in MACQU only through occasional user's interventions or in the rule base by expert rules (models have given off-line values for rules' premises) or rules communicating on-line with a production model. In a European research project (HORTIMED, 2000) research work is organized to provide enough data for Production Functions versus water quality in order to build a DSS, as a MACQU companion, to manage scarce waters and water recycle for Horticulture.

MACQU TOOLS AND METHODS

The greenhouse is a complex system and needs a number of control tools, at different levels, in order to provide a complete solution, without compromises. This section briefly describes the various control tools and methods offered by MACQU, as well as its capabilities as a virtual control environment.

At the heart of most computer programs lies a model of the problem domain. This model defines the entities that the program is designed to handle and describes their operational characteristics and state. For nontrivial systems, such as a modern greenhouse system, good practice is to separate functionally the system model from the management application. The development of such a model was started within the MACQU program as a parallel effort to the research and development effort.

The main innovative features implemented to provide a flexible system, like MACQU, are (for details, see Sigrimis et al., 2000b) :
· Functional objects
· Virtual variables (VV)
· Output drivers (OD)
· On-line optimization tool
· Presentation objects
· Data base
· Virtual control loops
· KBS-Tasks/subtasks

A pictorial view of how the above system functions and control objects are bound together to operate on a greenhouse process is given in Fig. 3. A rather typical virtual control loop is depicted in Fig. 4.

The central, PC Windows 95 based, MACQU software is intended to : a) provide menus to setup the GMS, b) feedback the user with real time graphics and c) manage the overall operation by few rules. The later is a fuzzy logic KBS subsystem, which can be used also to do control (i.e. a fuzzy PID). The fuzzy logic is primarily intended to provide management decisions. The modes of action of the KBS are (see Fig. 5) :
a. Direct control of equipment (i.e. emergency rules)
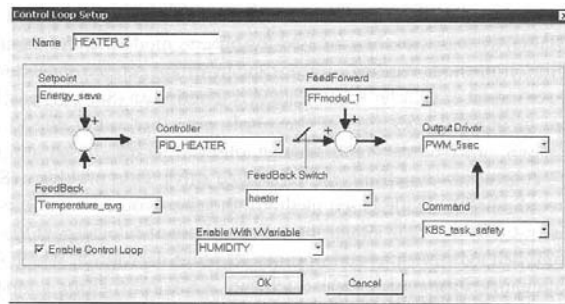b. Control decisions sent to replace the m value of a low-level loop (see Fig. 3). The loop
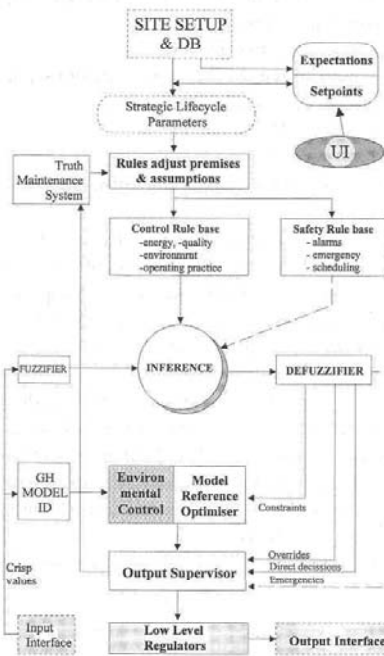
Fig. 4 A virtual control loop.

Fig. 5 MACQU KBS interfaces, fuzzy logic control and supervision.

is established in the KBS through rules.

c. Override the action of a low level loop through automatic enable/disable logical switches (i.e. start a sequence). Controller switching or reference switching is also possible based on a decision made by the KBS.

d. Set or adjust the constraints of a model based control loop. These are synergetic mechanisms where AI decision tools cooperate with conventional regulators (an example discussed in Sigrimis et al., 2000b).

In many physical processes, there is considerable interaction between the inputs

(manipulated variables) and the output signals (controlled variables). Multi_input_multi_ output (multivariable) systems can then be used for process modeling and control. Conventional control solution methods require a linear time invariant process characterization in the form of a state space model or transfer function matrix description (Sigrimis and Rerras, 1996). Such systems lead to optimal operation of the whole plant but suffer due to unpredictable inputs, non-linearities, uncertainties and change of user targets based on the situation. Adaptive and H$^\infty$ controllers can effectively be used to solve these problems (Sigrimis et al., 1999 ; Arvanitis et al., 2000). Rule based methods and fuzzy logic control are good alternatives to handle "non-linear algebra" situations. Formal use of rule bases at the high decision level allow for well defined strategies and optimal set-point derivation, which contribute the most to overall system performance. Hybrid schemes, i.e. a rule calling a model to provide an estimate before making a decision, are also possible. Other valuable control methods improving performance, i.e. feedforward disturbance compensation and variables' rate for PID, are also realizable in the fuzzy KBS, as in the following example :

IF outside_temp_falls_rapidly THEN
increase_little heating_water_temp

Regarding the GH as a multi-input, multi-output (MIMO) system, the approach used is to design the controllers and decoupler separately, i.e :

IF humidity is high THEN
increase_little air_temp_set_point

Figure 5 shows the interrelationship of different software components and the need for synergism.

Recently added technologies to support Internet Remote Connectivity and a Remote Camera have converted the MACQU system to a virtual control environment with educational but also commercial applicability. These advanced capabilities have been used to convert a real greenhouse to a virtual greenhouse, available to any authorized "visitor."

MACQU internet-accessed virtual greenhouse is based on a Client/Server computer configuration as it can be seen in Fig. 6. The user is located at the client side and can use any computer with Internet access. The server is a PC located near the greenhouse. The server sends to the client all requested measurements and transfers all set-up commands transmitted by the client to the MACQU controllers. The MACQU controllers are responsible for executing these commands and send to the server the new measurements and images. This configuration has the advantage that the controller handles all control locally. In this way, problems caused by network delays are avoided.

In our case the MACQU controller is installed in a greenhouse. All users have access to
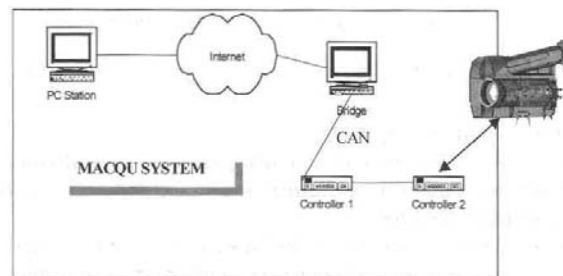

Fig. 6 Remote control case.
The PC station is connected to the controllers via Internet.

measurements and visual monitoring of the system at any time. Furthermore, they have access to the demo version which is the whole Server-based software, together with a controller emulator and a greenhouse model linked to it for setting up and trying different control laws, control loop configurations and whole scenarios.

Further support is available for a camera connected to a MACQU controller to send images of greenhouse interior to the remote PC through Internet. During a remote access of the VG the control logic runs in the controller but all system variables are available in the remote station for monitoring, using a rich set of presentation graphics. Thus the whole operation is transparent to the user, the controls run in real time locally in the VG and the results are available remotely, at the connection speed, without affecting the real mode operation. The channel throughput is divided by the user between monitoring data and camera frames.

Camera use is for:

a) Visual Monitoring the experiment or the greenhouse.

b) Managerial reasons (i.e. Inspection and Diagnosis of machinery, a Camera Sensor with good zoom to detect diseases, to measure growth and to become an advanced sensor in the future, electronic commerce between the grower and the consumer, advertising the product in the GH, etc.).

APPLICATION EXAMPLES

1. Low level control (Greenhouse heating control using the Load Divider concept)

A set of tests is first presented to highlight the capabilities of MACQU in implementing low-level control tasks. For analogous results regarding other control problems and alternative design techniques, see Sigrimis et al. (2000b), Pasgianos et al. (2001). These experiments used the MACQU-Climate system to control the temperature of the Rose Greenhouse of the Agricultural University of Athens (AUA). In the experiments, a Load Divider is used in cooperation with a supervisory tool to minimize the heat losses and achieve better temperature distribution around the plants.

The AUA Rose Greenhouse Heating System is depicted in Fig. 7. As it can be seen from this figure, there are two sets of heating pipes. The first set (P_1) is located at the lower part of the greenhouse and near the roots of the plants, while the second (P_2) is located approximately 2 m higher.

Each separate heating system includes an integrating triode valve, a circulator and a temperature sensor, in order to measure and control the two pipe temperatures, T_{P1} and T_{P2}, respectively. Three additional temperature sensors are placed near a plant: one at the lower part, near the roots (T_1), one at the middle (T_2) and one over the top (T_3) of the plant. The temperature of the greenhouse is controlled with reference to the temperature $T_{in} = T_2$.

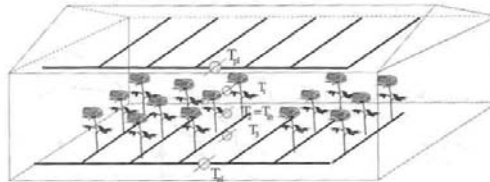The control objective here is to regulate the temperature T_{in} while minimizing heat losses

Fig. 7 Schematic diagram of the Rose Greenhouse Heating System.

and temperature differentiations near the plants. In order to minimize the heat losses, which are proportional to the average greenhouse temperature, the heating pipes are placed near the plants. This works well when the heat requirements are small (e.g. warm days) and the pipe temperature is small. However, when the pipe temperature is high, the bottom part will be very warm resulting to water or heat stress, while the top of the plant will be rather cold. This is due to the bad temperature distribution. In order to improve the temperature distribution, one has to add a second set of heating pipes at a higher position. The problem with this configuration is how to manipulate (divide and apportion) the needs in heat (*Load*) to the two heating subsystems. One solution is to use two control loops, one for each subsystem. The control loop relative to the lower pipe regulates the temperature at the lower part of the plant, while the control loop of the upper one, is devoted to temperature regulation at the higher part of the plant. · With this configuration, a multivariable system is obtained, which, obviously, is more complicated and difficult to analyze and control.

In order to avoid the inherent complexity of multivariable control, we next propose using only one control loop and, furthermore, applying a '*Load Divider*' to apportion the load to the two pipes.

In control systems for which, more than one actuator contribute to each control input, it is very useful to incorporate (when possible) a mechanism that divides the input needs (*Load*) to each actuators. Examples of such cases are:

a. systems incorporating two or more different types of input actuators (e.g. hybrid cars, where power is supplied by both electric and fuel engines, heating and air-conditioning systems, power systems, etc.),

b. systems exhibiting large variations in load needs as well as increased accuracy and robustness in manipulating both trivial and substantial loads (e.g. fertigation systems with numerous irrigation lines),

c. systems in which each actuator contributes to the load at a different manner (e.g. the present heating control case).

The concept of the Load Divider provided by the MACQU system and used in the experiments described below, is depicted (Fig. 8).

This Load Divider incorporates two threshold points A_1 and A_2. Values of the load L being lower than A_1 are ignored (hysteresis). Usually, in order to guarantee linearity $A_1=0$. When L is lower than A_2, only the first actuator is active. The second actuator becomes active for values of L greater than A_2. The values of the two split loads are given by

$$L_1 = \begin{cases} 0 & L \le A_1 \\ L & A_1 < L \le A_2 \\ A_2 + \dfrac{L_{1\max} - A_2}{1 - A_2}(L - A_2) & A_2 < L \le 1 \end{cases}$$
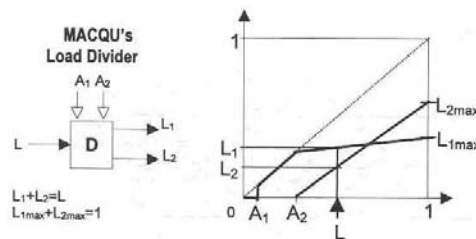

Fig. 8 MACQU's Linear Load Divider.

and

$$L_2 = \begin{cases} 0 & L \le A_2 \\ \dfrac{L_{2\max}}{1-A_2}(L-A_2) & A_2 < L \le 1 \end{cases}$$

where $L_{1\max}$ and $L_{2\max}$ are the maximum loads encountered by the two actuators. Note that $L_1 + L_2 = L$, for all values of the load, greater than A_1. The normalized loads for each actuator are given by

$$L_1^* = \frac{L_1}{L_{1\max}} \quad \text{and} \quad L_2^* = \frac{L_2}{L_{2\max}} \tag{1}$$

Figure 9 shows the control configuration used in our experiment, in order to control the greenhouse temperature. The system control input is the heat produced by the two pipes. This heat is proportional to the difference between the pipe temperatures (T_{P1} and T_{P2}) and the temperature of the greenhouse T_{in}. Two PID based nested loops are used here, in order to control temperatures T_{P1} and T_{P2} of the two pipes. Changes in pipe temperatures are achieved through a PWM output driver, with the duty to manipulate the triode valve position.

As it is shown in Fig. 9, the outer control loop consists of a feed-forward component and a PID based feedback loop. The load produced by this controller is split to the two heating subsystems, by the Load Divider. A normalizer and a mapper are used in each case in order to transform the load needs into pipe temperatures. The normalizer is used to calculate the normalized loads given by Eq.(1), while the mapper calculates the pipe temperatures, on the basis of the following relation

$$T_{Pi} = T_{in} + (T_{Pi\max} - T_{in})L_i^* \quad (i=1,2)$$

where $T_{Pi\max}$ is the maximum temperature allowed for the ith subsystem (e.g. the temperature of the pipe located near the roots of the plant cannot exceed a user prespecified maximum value, i.e. 50°C).

It is a standard practice, in tuning of control systems with nested loops, to start from the inner loop and then proceed to the outer ones (Astrom and Hagglund, 1995).

The triode valves used here to adjust the temperature of the two pipes are integrator type. The gain K_V of this integrator, is simply calculated from the time needed to turn the valve from the fully closed to the fully open position. In our case, for both valves, this time was 60 s. Thus, the gain $K_V = 1/60 \text{ s}^{-1}$. This integrator is used as the integrator of the velocity form PID, implemented by the MACQU system, and given in discrete form by (Astrom and Hagglund, 1995)
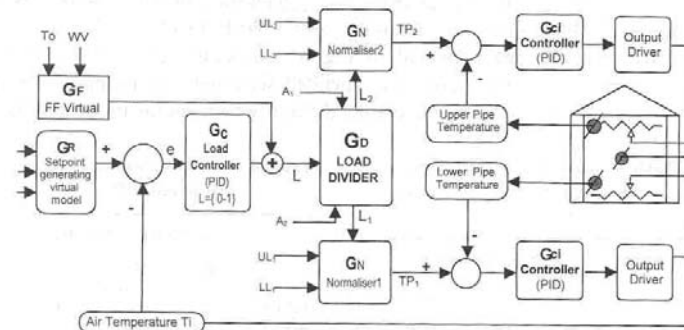

Fig. 9 Nested Loop Control configuration using the Load Divider.

$$u(k)=K_V\cdot\sum_{j=0}^{k}[(K_P+t_sK_I+t_s^{-1}K_D)e(j)-(K_P+2t_s^{-1}K_D)e(j-1)$$
$$+(t_s^{-1}K_D)e(j-2)] \qquad (2)$$

where t_s is the sampling time, $e(k)$ is the error at the time kt_s and K_P, K_I K_D are the proportional, integral and derivative gains of the PID controller. Note that the discrete integral term $K_V\times\Sigma$ is implemented by the rotation of the valve.

The pipe system is assumed to be, a first order plus dead time (FOPDT) system with a transfer function

$$H_{Pi}(s)=\frac{k_{Pi}e^{-d_{Pi}s}}{st_{Pi}+1} \qquad (3)$$

where k_{Pi}, t_{Pi} and d_{Pi} are the gain, time constant and time delay relative to the ith pipe, respectively. When the parameters of Eq.(3) are identified, the values of the PID gains in Eq. (2) are calculated and the two inner loops are closed. The next step of the control procedure, is to identify the entire heating system, assuming that it is also a FOPDT system with a transfer function of the form

$$H_{Tp2}(s)=\frac{k_{Tp2}e^{-d_{Tp2}s}}{st_{Tp2}+1} \qquad (4)$$

With the parameters obtained for Eq.(4) the outer PID is tuned. The discrete form of the PID is

$$u(k)=K_C\left[e(k)+\frac{t_s}{t_I}\sum_{j=0}^{k}e(j)+\frac{t_D}{t_s}\{e(k)-e(k-1)\}\right] \qquad (5)$$

where K_C, t_I and t_D are the controller gain, the integral reset time and the derivative time, respectively. The feed-forward controller has the form

$$u_F(k)=K_F(T_{sp}-T_{out})$$

where K_F is a constant gain and T_{out} is the outside temperature.

A step response identification experiment was performed first, in order to identify the parameters of Eq.(3) for the two heating subsystems. In this experiment the temperature T_{in} of the greenhouse is assumed constant and the sampling time was chosen $t_s=1$ s. A five sample average filter is also used, in order to accommodate the measurement noise. The time delay added by this filter is identified as part of the overall system delay. Since the system is assumed to be linear, the step response test was performed by turning the triode valve from the fully closed to the fully open position (i.e. a step from 0 to 1). From these responses, the parameters identified for the two pipe systems are presented in Table 1.

With these parameters, the gains of the two PID controllers were selected using extensive simulation and the requirements that the two inner systems must be overdamped (Astrom and Hagglund, 1995). Table 2 shows the obtained gains. With these controller gains, the two closed loop step responses are presented in Fig. 10. In order to measure the two load capacities, L_{1max} and L_{2max}, each pipe was operated separately, at its maximum allowed temperature T_{Pimax}. The maximum temperature difference between the inside and the outside

Table 1 Identified system parameters for the two pipe systems.

	System parameters		
	d_{Pi}	t_{Pi}	k_{Pi}
Pipe 1	30 s	110 s	65°C
Pipe 2	28 s	98 s	69°C

Table 2 Controller gains for the two nested PIDs.

	Controller parameters		
	K_{Pi}	K_{Ii}	K_{Di}
PID 1	3	0.03	1
PID 2	2.5	0.04	1

temperature $(\max \Delta T)_{Pi} = \max(T_2 - T_{out})_{Pi}$ at the steady state defined the load capacity of each subsystem. The load $L_{i\,max}$ is given by

$$L_{i\,max} = \frac{\max(T_{in} - T_{out})_{Pi}}{\max(T_{in} - T_{out})_{P1} + \max(T_{in} - T_{out})_{P2}}$$

With $T_{P1\,max} = 50°C$ and $T_{P2\,max} = 80°C$, the measured load capacities are $L_{1\,max} = 7.5°C/19.8°C = 0.38$ and $L_{2\,max} = 12.3°C/19.8°C = 0.62$.

In order to identify the entire system, we perform a relay feedback experiment. From this
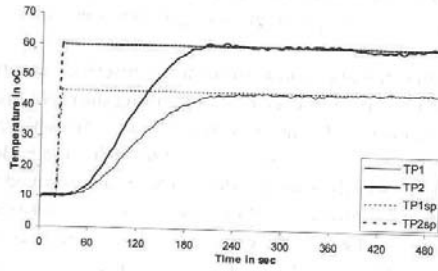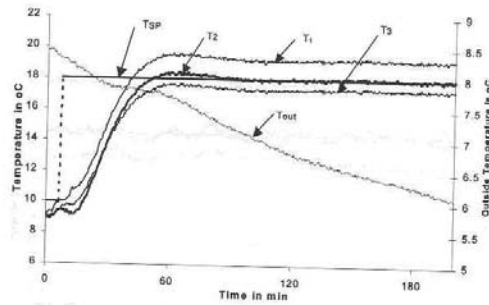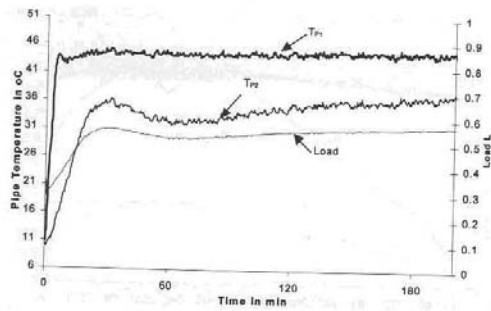

Fig. 10 Closed-loop step response of the two pipe systems.

(a)

(b)

Fig. 11 a) Close loop temperature step response.
b) Pipe temperatures and load.

experiment the average ultimate period was measured as $P_u = 1\,750$ s and the average ultimate gain as $K_u = 4.7°C$. With the above information, the Tyreus and Luyben method (Astrom and Hagglund, 1995), was next applied, in order to calculate the parameters of the PID controller in Eq.(5). These parameters are $K_C = 2.1364$, $\hat{o}_1 = 3\,850$ s, $\hat{o}_D = 277.8$ s. The gain of the feed-forward controller was selected as $K_F = 0.045$.

With the controller parameters obtained above, a step response experiment was first performed. The results are presented in Fig. 11a and b. In Fig. 11a, the temperatures T_1, $T_2 = T_{in}$, T_3 as well as the outside temperature T_{out} (secondary axis) are shown, while Fig. 11b presents, the temperatures of the two pipes and the total load (secondary axis), as computed by the load controller.

These figures show that the maximum temperature difference around the plant is always lower than 2°C. It is also apparent that as T_{out} drops along the night the load L increases and the increase is mostly taken up by T_{P2} and less by T_{P1}. This bears the meaning of protecting the plants from overheating the nearby pipes T_{P1}. This behavior is defined by the selected thresholds $A1$ and $A2$ (Fig. 8) of the load divider. This is also verified in Fig. 12a, where the same temperatures are recorded, during a whole night in regular operation. Although there is a variation of almost 6°C in the outside temperature, there is no significant variation in the temperature distribution around the plant. Finally, in Fig. 12b, the two loads L_1 and L_2, produced by the Load Divider are presented together with the pipe temperatures.
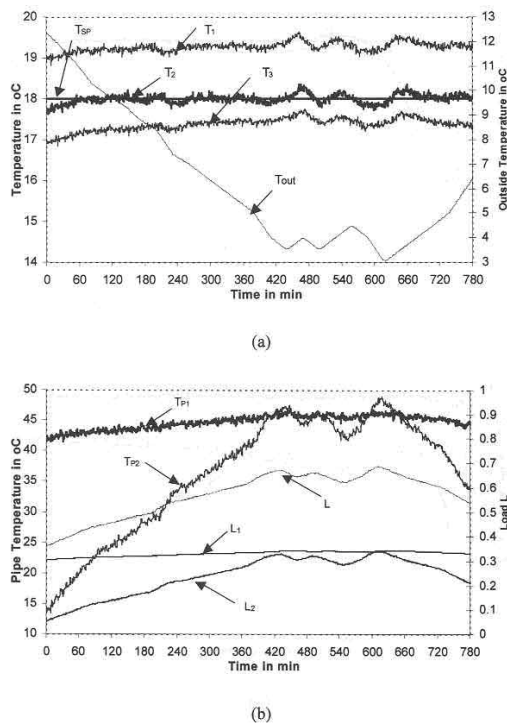

(a)

(b)

Fig. 12 a) Closed loop temperature regulation during a whole night and b) Pipe temperatures, the total load L and the two split loads L_1 and L_2 apportioned by the Load Divider.

2. Medium level control (Irrigation tuning using the optimization tool)

In this section, an approach for irrigation management is presented as an example of the medium-level-control capabilities of MACQU system. A crop transpiration model of a convenient form is used to predict the necessary supply of water (for details, see Sigrimis et al., 2000a, 2001). A hydroponic system is operated and the drain water flow from the crop is measured using an appropriate device (a tipping bucket). Using the error between drain measurement and model estimate the coefficients of the model are iteratively adapted. The adaptation process is continuous and on-line, so that the model adapts for seasonal variation of crop growth.

The MACQU optimization tool was used to train on-line a linear perceptron of the form depicted in Fig. 13. The optimizer module is an iterative search algorithm that can adjust the model parameters in order to minimize a specified error metric. The algorithm is an enhanced variation of the Hooke–Jeeves (Shoup, 1979) minimization algorithm, and is embedded for general use in the MACQU greenhouse control software. Results from field applications of this MACQU tool, after only 3 days of model "learning" period, are shown in Fig. 14. The accuracy of the computed water consumption, and irrigation control based on the computed transpiration, was better than 3% with every irrigation cycle.
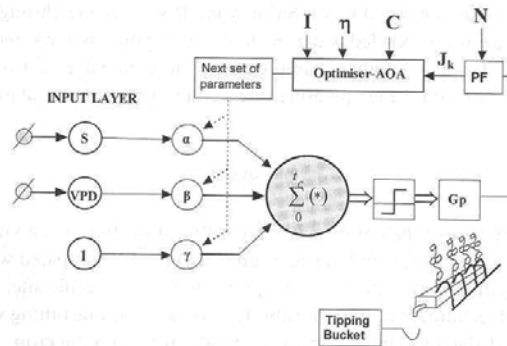

Fig. 13 A simple linear perceptron for learning of the crop transpiration model.
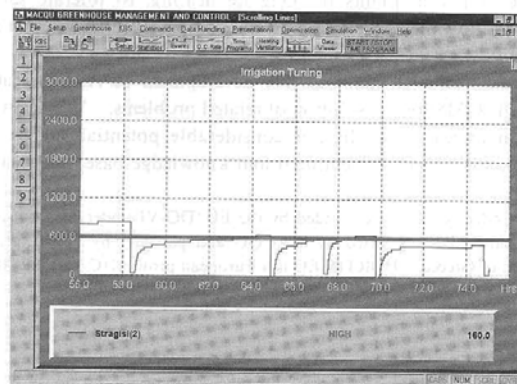

Fig. 14 Irrigation water management using on-line tuning of a Transpiration model, in MACQU.

3. High level control and supervision

At the outer loop (Fig. 2) the practice until now was to produce "blue-print" rules, from experimental results, and let the grower follow these rules along the crop season.

Contemporary greenhouse operations require precise control of irrigation and nutrient supply in order to optimize crop growth and minimize cost and pollution due to effluents. Moreover, in Mediterranean countries there is a need to minimize water waste due to seasonal shortages. In modern greenhouses nutrient supply is computer controlled and based on measuring salinity and compensating deficiencies by a mix of clean water and two 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 fact is that specific ion Nutrient Uptake (NU) is not measured and the system is monitored every so often (i.e. every 15 days) by manual analytical measurements and adjustment of the stock solutions. Presently the number of stock solutions is increased above the basic two (A and B tanks) with compensating solutions tanks composed of ions that exhibit variation in Uptake with growth stage and/or weather conditions. The drain water is analysed by on-line using ISFET sensors and the "recipe" is adapted to compensate the NU variation. Such work is being undertaken by a project (HORTIMED, 2000) to provide NU models that can help do "predictive recipe adaptation," until ISFET technology becomes practically usable. Furthermore the HOR-TIMED project elaborates on Yield versus Salinity models to be able, through MACQU tools, to effectively manage on-line recycled water in closed hydroponic systems, based on physiological (NU) models and cost. Another example of high level management is the possibility of saving energy costs, based on the temperature integrating capabilities of plants (Sigrimis et al., 2000c).

DISCUSSION

The preliminary tests of the optimization algorithm show that it is a viable alternative to the techniques used for irrigation and nutrient supply control. Compared with robust control designs it requires virtually no effort for its application on a specific site. Compared with model based control techniques it offers the ability of on-site, on-line tuning which removes the need for exact knowledge of plant transpiration model for a specific crop.

An advanced management system such as MACQU provides both practitioners and researchers with several interesting capabilities. Combined with expert knowledge of plant physiology (i.e. the ability of plants to integrate heating, to tolerate salinity, etc.) these advanced capabilities allow the user to realize significant benefits in both cost expenditures and crop yield and quality.

The MACQU environment facilitates the development of AI applications capable of collaborating with the GMS for the solution of related problems. While little work has been done in this area, it appears that there is considerable potential for the development of intelligent systems that combine conventional and knowledge based applications.

REFERENCES

Arvanitis, K. G., Paraskevopoulos, P. N., Vernardos, A. A. 2000. Multirate adaptive temperature control of greenhouses. Comput. Electron. Agric. **26** : 303–320.

Astrom, K. J., Hagglund, T. 1995. PID Controllers : Theory, Design and Tuning. ISA Transactions. Research Triangle Park, N. C.

Garcia, J. L., De la Plaza, S., Navas, L. M., Benavente, R. M., Luna, L. 1996. Evaluation of the feasibility of alternative energy sources in greenhouse heating. AgEng International Conference on Agricultural Engineering, Madrid.

Gieling, T. 1997. Monitoring and control of the supply of water and nutrients. MACQU/AIR Program II Final Report.

HORTIMED 2000. European Research project ICA3-1999-000009, coordinated by Dr. N. Sigrimis mailto : n.sigrimis@computer.org.

Jolliet, O., Bailey, B. J. 1995. The effect of climate on tomate transpiration in greenhouse measurements and models comparison. Agric. For. Meteorol. **58** : 43–62.

Pasgianos, G. D., Arvanitis, K. G., Sigrimis, N. 2001. A non-linear feedback technique for greenhouse environmental control. Prepr. IFAC Workshop on Artificial Intelligence in Agriculture (AIA' 2001), June 6–8, Budapest, Hungary, p 109–116.

Shoup, T. E. 1979. A Practical Guide to Computer Methods for Engineers. Prentice Hall, Inc., Englewood Cliffs, N. J.

Sigrimis, N., Rerras, N. 1996. A linear model for greenhouse control. Trans. ASAE **39** : 253–261.

Sigrimis, N., Arvanitis, K. G., Kookos, I. K., Paraskevopoulos, P. N. 1999. H∞-PI controller tuning for greenhouse temperature control. Proc. 14th Triennial IFAC World Congress, Vol. K, July 5–9, Beijing, China, p 485–490.

Sigrimis, N., Arvanitis, K. G., Gates, R. S. 2000a. A learning technique for a general purpose optimizer. Comput. Electron. Agric. **26** : 83–103.

Sigrimis, N., Arvanitis, K. G., Pasgianos, G. D. 2000b. Synergism of high and low level systems for the efficient management of greenhouses. Comput. Electron. Agric. **29** : 21–39.

Sigrimis, N., Anastasiou, A., Rerras, N. 2000c. Energy saving in greenhouses using temperature integration : A simulation survey. Comput. Electron. Agric. **26** : 321–342.

Sigrimis, N., Arvanitis, K. G., Pasgianos, G. D., Ferentinos, K. P. 2001. Hydroponics water management using adaptive scheduling with an on-line optimizer. Comput. Electron. Agric. **31** : 31–46.

Stanghellini, C. 1987. Transpiration of greenhouse crops, an aid to climate management. PhD thesis, Agricultural University, Wageningen, pp 150.

Weng, C., Ray, A. 1997. Robust wide-range control of steam electric power plants. IEEE Trans. Control Syst. Technol. **5** : 74–88.