NEURO-DYNAMIC PROGRAMMING-BASED OPTIMAL CONTROL FOR CROP GROWTH IN PRECISION AGRICULTURE

J. Pucheta, H. Patiño, R. Fullana, C. Schugurensky and B. Kuchen

Instituto de Automática, Facultad de Ingeniería, Universidad Nacional de San Juan
Av. Libertador 1109 (O), 5400 San Juan, ***Argentina. E-mail:*** ipucheta@inaut.unsj.edu.ar

Abstract: In this paper, a neuro-dynamic programming based optimal controller for crop-greenhouse systems is proposed. The neurocontroller drives the crop-growth development minimizing a predefined performance index, which considers minimization of the greenhouse operative costs and the final state errors under physical constraints on process variables and actuator signals. In particular, it is applied to guide the tomato-seedling crop development through control of a greenhouse microclimate. In the neurocontroller design process non-linear dynamic behavior of the crop-greenhouse system and the July climate data of 1999 of San Juan, Argentina, are considered. In order to show the practical feasibility and performance of the proposed neurocontroller, simulation studies were carried out for the guidance of the tomato-seedling crop.

Keywords: optimal control, neural networks, dynamic programming, agricultural production management.

1. INTRODUCTION

Agricultural production management and control systems are becoming highly sophisticated and are beginning to exploit many of the advanced methodologies and tools of industrial automation and modern control systems theory, which integrates mechanical, electronic, computer, and information systems. The agricultural sector is one activity of the major importance in Argentina and management and control systems are an important subject of research.

The growth and development speeds of greenhouse crops are affected by inside climatic conditions such as temperature, humidity, carbon dioxide (CO_2) and solar radiation. These greenhouse microclimatic variables can be manipulated in order to guide the crop-growth development reaching some predefined technical and economical objectives. For instance, to obtain certain production according to a production schedule within a predefined period and with the lowest cost possible or greatest profits. In addition, the final product should have certain characteristics imposed by the market such as weight, number of nodes, number of leaves, color, size or others.

Another aspect to take into account is that each crop imposes their own particular constraint to the ranges of variation of climatic conditions; for instance, with temperatures below a minimal level seedlings stop growing, and with temperatures above a maximum level they can suffer irreversible damage. Thus, it is very important to reach internal climatic conditions (set points) following an appropriated trajectory, which takes the seedlings from an initial state to a desired final state minimizing a cost index o cost function, in a predefined time, and considering the climate constraints imposed by the particular crop. The generated trajectory will be optimal with respect to that criterion function defined for each particular case. Therefore, the main problem is to obtain an optimal decision policy in order to get that optimal set points trajectories (Hwang and Jones, 1993). Solution to that problem may be faced using optimal control theory (Lewis and Syrmos, 1995; Kirk, 1970).

Several methods have been used to obtain optimal trajectories of control variables in the guide of crop growth, which in general are based on the Principle of Maximum of Pontryagin (Ioslovich *et al*, 1995; Seginer *et al*, 1991; Seginer and McClendon, 1992). Methods for sequential search of the optimal control actions can be seen in Ioslovich *et al* (1995), using Linear Programming in Gutman *et al* (1993), and Dynamic Programming in Fullana and Schugurensky (1999) and in Pucheta *et al* (2001).

In this paper, a neuro-dynamic programming based optimal controller for crop-greenhouse systems is proposed. Neuro-dynamic programming enables a system to learn how to make good decisions by observing its own behavior and to improve its actions by using a built-in mechanism through reinforcement (Bertsekas and Tsitsiklis, 1996). This design methodology exploits the capability of neural networks for learning nonlinear functions to solve the drawback of the curse of dimensionality present in the dynamic programming-based optimal control problems. The proposed control law minimizes a predefined performance index, considering the minimization of operative costs and terminal state errors. The neurocontroller is able to guide the tomato-seedling crop development under physical constraints on process variables and actuator signals (Lapilli *et al*, 2001; Seginer and McClendon, 1992). Tomato is an important crop in the agricultural production at San Juan, Argentina. The dynamic model of the crop-greenhouse system is characterized by a set of nonlinear differential equations with boundaries and under strong external disturbances, the July climate data of 1999 of San Juan (Argentina) (Pucheta *et al*, 2001), which is used to design the neurocontroller minimizing operative costs and final state error. The control law obtained in the design process results suboptimal, due to the use of neural networks to approximate both the optimal cost-to-go function and the optimal policy.

In order to show the practical feasibility and performance of the proposed neurocontroller, simulation studies were carried out for the tomato-seedling crop development, which would ease the transition to experimentations on a scale model of a greenhouse available in the Instituto de Automática's laboratory.

2. PROBLEM FORMULATION

Jones (1991) develops a dynamic model of tomato growth (the TOMGRO model), and shown that crop development can be guided if suitable set points are established to the environment variables, considering that other factors as air RH, irrigation, nutrients, pesticide have being managed, which do not influence on the normal crop growth. In this work it is used the tomato growth dynamic model proposed by Jones, and to guide the crop growth two environment variables of the greenhouse are used as control actions, temperature and CO_2 concentration. The optimal control problem of the crop growth can be formulated as follows. By considering the dynamic model of the crop-greenhouse system, it is desired to obtain autonomously a sequence of optimal control actions (values of heater use and window opening and CO_2 set points) such that the crop growth goes from an arbitrary initial state condition to a desired final state by minimizing a predefined costs functional.

The tomato crop growth can be characterized by non-linear dynamic model with two-state variables, dry weight and number of leaves,

$$\begin{cases} \dfrac{dN}{dt} = r_m r(T) \\ \dfrac{dW}{dt} = E\big(P_g(T) - R_m(T)W\big) \end{cases} \tag{1}$$

where N(t) is the number of leaves and W(t) is the total dry weight of the crop in [g m^{-2}]. In addition, r(T) is a piecewise linear temperature function, based on the TOMGRO model, $R_m(T)$ and $P_g(T)$ (both as function of the temperature T) are the sustainable respiration rate of the leaves in g [CH_2O] g^{-1}[tissue] h^{-1}, and the canopy gross photosynthesis rate in g [CH_20] m^{-2} [ground] h^{-1}, respectively. The coefficient r_m is the maximum rate of leaf appearance per hour, and E is the conversion efficiency of CH_2O to plant tissue, g [tissue] g^{-1}[CH_2].

The greenhouse modeled in (Lapilli *et al*, 2001) by

$$\begin{cases} T = To + \dfrac{bS_0^{\lambda}}{(U + Q_v)} & \text{if } F_c = 0 \\ T = To + \dfrac{bS_0^{\lambda} + F_c}{U} & \text{if } Q_v = 0 \end{cases} \tag{2}$$

where T and To are the internal and external temperature [°C], respectively. The function So is the global solar radiation in [W m^{-2}], the coefficient b is the global solar energy fraction that contributes to the increase of T, b≅1m2, λ=0.45 is an empirical coefficient and U=0.5056 is the energy loss coefficient by interacting with the environment in [W °C-1]. The variables Fc and Qv are used as control actions, where Fc = F.H(t) with H(t) ranging between 0 and 1, F is the heating coefficient, 14.966 [W], and $Q_v = 0.107 \cdot V(t) + 2.3275 \cdot V(t)^2 - 1.2761 \cdot V(t)^3$ where V(t) is the windows action, dimensionless ranging between 0 and 1.

This greenhouse model is an algebraic model that does not have state variables, which control actions or manipulated variables are the percentage of use of heater, F_c, and opening windows, Q_v.

The model of Eq. (2) considers that the heating and ventilation variables are mutually precluding (one excluding the other). Thus, the two manipulated variables, H(t) and V(t) -that range between 0 and 1- are grouped into only one variable ranging between -1 and 1.

$$V(t) = -\min\{0, a(t)\}$$
$$H(t) = \max\{0, a(t)\} \quad (3)$$
$$\text{where } -1 \le a(t) \le 1$$

The control of air moisture content within the greenhouse is done independently. This is so because seedlings require minimal moisture content, and the need to decrease it may eventually arise when the seedling is almost ending the guidance process.

Equations (4) and (5) are the performance index and the cost function to be minimized.

$$I(\mathbf{x}, \mathbf{x}_d, \mathbf{v}) = \Lambda \cdot \mathbf{v} + \theta_1 \cdot P_r + \theta_2 \cdot P_W \quad (4)$$

$$J(\mathbf{x}, \mathbf{x}_d, \mathbf{v}) = \int_t^{t_f} I(\mathbf{x}, \mathbf{x}_d, \mathbf{v}) d\tau + \Gamma \cdot |\mathbf{x} - \mathbf{x}_d| \quad (5)$$

where:

$\mathbf{x}_d = [w_d \quad N_d]^T$ is the desired final values for the state variables,

$W_d = 0.21$ g m^{-2} the desired final dry weigh,

$N_d = 3$ desired number of leaves,

Λ, θ_1 and θ_2 are weighing coefficients with $\Lambda = \begin{bmatrix} 1000 & 0 \\ 0 & 0.05 \end{bmatrix}$, $\theta_1=50$, $\theta_2=50$,

P_r is a nonlinear function to constrain the internal temperature defined by

$$P_r = \begin{cases} [T - 36] & \text{if} \quad T > 36 \\ [8 - T] & \text{if} \quad T < 8 \\ 0 & \text{if} \quad 8 \le T \le 36 \end{cases} \quad (6)$$

P_W is a nonlinear function to avoid any overshoot in the desired dry weight

$$P_W = \begin{cases} [W(t) - W_d] & \text{if} \quad W(t) > W_d \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

$\mathbf{v}(t) = [C_f(t) \quad C(t)]^T$ is the costs vector associated to the control actions,

$C_f(t) = H(t) \cdot P_c$, with P_c = \$ 0.12 h^{-1} (cost of heater action), $C(t) = K_{CO2(t)} \cdot P_{co2}$, P_{co2} is the cost of the C(t) injector action. The expression of the proposed cost function is plotted in Fig. 1, showing the cost approximation surface generated by the control actions.

In order to apply the neuro-dynamic programming in the neurocontroller design it is necessary to replace the continuous spaces of the problem by a discrete space with a finite number of elements, involving a finite number of states and decisions. Considering the transformation of x into itself by the system equations, which is applied at different time instants, k=0,1,…,N-1, to produce the sequence of states [$\mathbf{x}$(0), $\mathbf{x}$(1),…,$\mathbf{x}$(N-1)]. The index k of that sequence will be called the *stage variable.* Thus, the evolution of the process can be quantized in stages, denoted by k. The dynamic programming algorithm, and in particular neuro-dynamic programming, allows to deal with any differential equation properly quantized.

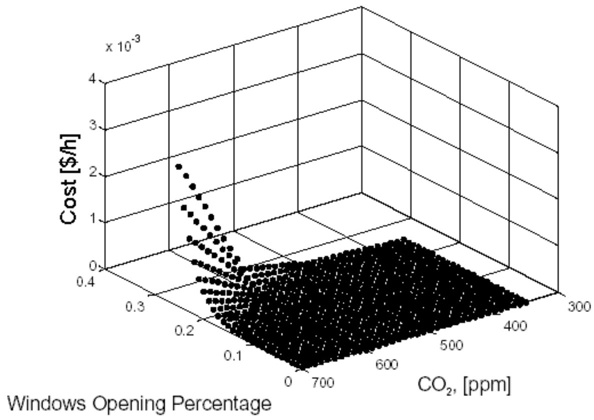

Fig. 1. Cost function in terms of CO_2 enrichment and windows opening percentage.

Now, considering that the system model depends not only upon the state $\mathbf{x}$ and stage k, but also upon a decision $\mathbf{u}$. It is assumed that the decision u is selected from a finite set of admissible decisions obtained quantizing $\mathbf{u}$ to a finite number of vales. The sequence of elements [$\mathbf{u}$(0),$\mathbf{u}$(1),…,$\mathbf{u}$(N-1)] is called the decision or control action sequence, which has the associated monetary costs sequence [$\mathbf{v}$(0),$\mathbf{v}$(1),…,$\mathbf{v}$(N-1)]. Therefore, an immediate question that arises is the determination of a rational for selecting the decision sequence. Consequently, the Eq. (5) can be rewritten as follows:

$$J(\mathbf{x}, \mathbf{x}_d, \mathbf{v})_k = I(\mathbf{x}, \mathbf{x}_d, \mathbf{v})_k + J(\mathbf{x}, \mathbf{x}_d, \mathbf{v})_{k+1} \quad (8)$$

The performance index $I(\mathbf{x},\mathbf{x}_d,\mathbf{v})_k$ is evaluated along each stage, called stage's cost, and the optimal cost functional will be the sum of the $I(\mathbf{x},\mathbf{x}_d,\mathbf{v})_k$ values along all stages. And the optimal control problem consists in determining an optimal decision sequence to minimize (or maximize) J.

3. BACKGROUND IN NEURO-DYNAMIC PROGRAMMING

The objective of dynamic programming is to evaluate numerically the optimal cost-to-go function J^*. This computation can be done off-line, i.e., before the real system begin operation. Fig. 2 shows the process evolution from the stage k to k+1, which evolves from state i to j by application of action $\mathbf{u}$ with an associated cost of I(i,$\mathbf{u}$). Both i and j have the cost-to-go value of J(i) and J(j), respectively. An optimal policy μ, that is, an optimal decision of $\mathbf{u}$ for each i, is computed either simultaneously with J^*, or in real time (Bertsekas, 1995; Casti and Larson, 1978) by minimizing the right-hand side of Bellman's equation (9). It is well known, however, that for many important problems the computational requirements of dynamic programming are overwhelming, because the number of states and control actions is very large *(Bellman's curse of dimensionality).* In such situations is more suitable to consider approximation or suboptimal control schemes in order to reduce the computational requirements.

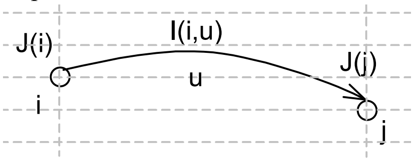

Fig. 2. Numerical computation scheme for stages k and k+1.

$$J(i)_k = I(i,\mathbf{u})_k + J(j)_{k+1} \tag{9}$$

Neuro-dynamic programming enables a system to learn how to make good decisions by observing its own behavior, and to improve its actions by using a built-in mechanism through the use of an iterative optimization scheme (Bertsekas and Tsitsiklis, 1996). This is an alternative optimization method to deal with the *Bellman's curse of dimensionality*, which is based on approximations of the dynamic programming algorithm. In addition, the neuro-dynamic programming is an attractive and suitable technique to design a simple control system, which can be implemented using small equipment, and resulting low investments. This fact is an important factor to be considered when there is a low profit margin, as does frequently in agriculture business.

Within the framework of the dynamic programming algorithms used to evaluate the optimal cost-to-go function is the *Policy Iteration* algorithm. In order to run the approximate policy iteration algorithm, an initial policy is required. In practice, it is usually important that this policy be as good as possible through heuristics or other considerations. In the absence of such a policy, we may fix a parameter vector of the neural network and then use a corresponding greedy policy.

The policy iteration algorithm fixes a policy μ, evaluates the associated cost-to-go function J^{μ}, and then performs a policy update. This methodology is often called as *actor/critic* systems. The actor uses a policy μ to control the system, while the critic observes the consequences and tries to compute J^{μ}. In addition, the actor uses the J^{μ}, received from the critic, in order to update its policy. For the standard version of policy iteration, the policy or control law μ is fixed for a long time and the critic's computations converge to J^{μ}. At that point, the limit J^{μ} is passed to the actor who takes J^{μ} into account and forms a new policy, by performing the minimization in the right-hand side of Bellman's equation; that is, at each state j, an action **u** is chosen that minimizes the proposed cost function.

In this work, the neurocontroller inputs are dry weight of the tomato-seedling crop, number of leaves, and stage. The outputs are the heater use or windows opening a(t), associated to temperature, defined by (3), and the CO_2 concentration.

A simulation study has been carried out using the crop-greenhouse system dynamic model presented in Section 2 in order to show the feasibility and performance of the proposed neurocontroller. In particular, it is considered the tomato seedlings growth and the July weather data of 1999 of San Juan (Argentina) as external climate. The field experience in San Juan has shown that a good tomato seedling must have a dry weight of 0.21 g and a number of leaves of three. Thus, 0.21 g and 3 leaves are the final state to be reached by the optimal trajectory of the control actions. The dry weight was constrained to the 0 – 0.21 g range, and T(k) in the range of 8 ^{o}C and 30 ^{o}C, which is the admissible temperature range for tomatoes.

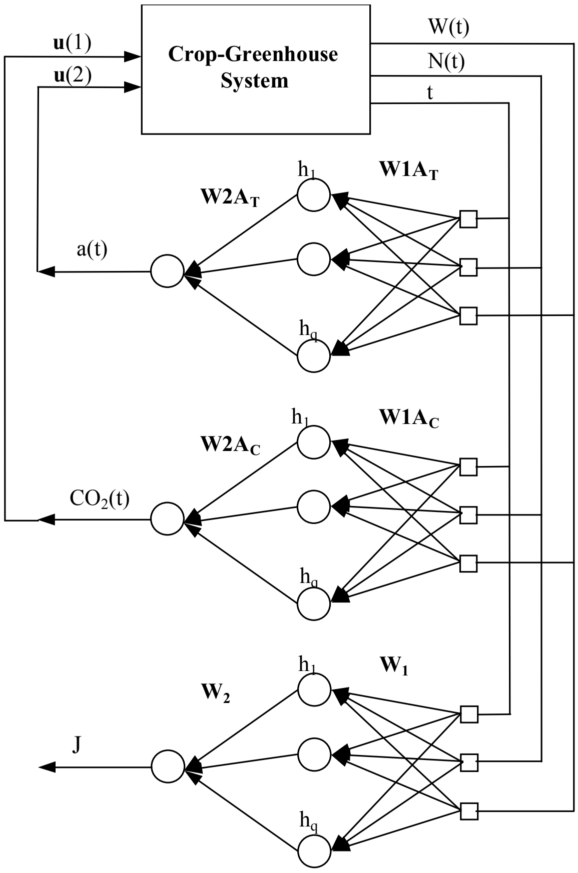

Fig. 3. Actor/critic scheme of the neurocontroller.

The two networks (CRITIC and ACTOR) are all implemented using multilayer feedforward neural networks of two layers with 9 neurons in the hidden layer. The neural network actor has 3 inputs, dry weight of the tomato seedling, number of leaves, and stage, and two outputs a(t) and CO_2 concentration. The CRITIC has the same inputs and one output, the cost-to-go function approximation. The CRITIC network output J, and the ACTOR network output **u** are trained according to the scheme presented in Section 3. The performance index and the cost function to be minimized were given by (4) and (5) respectively. The neural network structures are shown in Fig. 3. The Levenberg-Marquardt 's algorithm was used to train the neural networks (Bishop, 1995; Nørgaard, 1997). After the training process the ACTOR neural network is used on line to control the crop-greenhouse system according to Fig. 4.

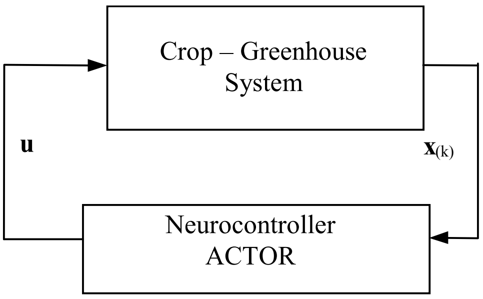

Fig. 4. Scheme of the on-line optimal control.

4. NUMERICAL RESULTS

The following figures show the crop-greenhouse system's evolution under several conditions, imposed by the San Juan real weather during July of 1999. The solid line trajectories (—Calculated) corresponds to the crop evolution (evolution of plant dry weight and number of leaves) considering the weather signal without perturbations. Fig. 5 represents the system evolution considering modifications in the weather model (system under perturbations). The dotted line trajectories (···5 days error) and dash-dot lines (-·-·-4 days error), show the effects of weather changes when it is shifted a fixed quantity (4 or 5) days from the present date.

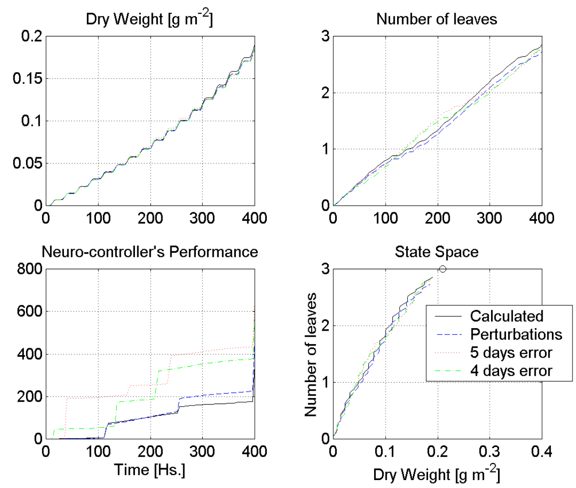

Fig. 5. Evolution of the crop state variables.

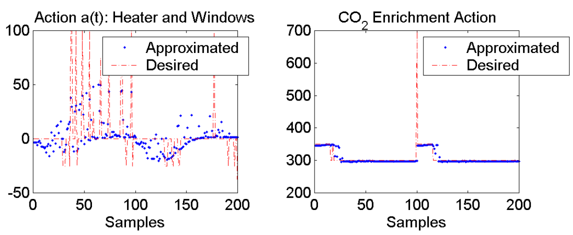

Fig. 6 Final evaluation of the approximated optimal policy.

The performance of the on-line neurocontroller deteriorates when changes the meteorological condition with respect to those used in the off-line calculation. The *correlation* concept is used to measure the difference between the meteorological conditions of calculation (off-line, Fig. 3) and those imposed at the moment of the on-line control (Fig. 4). It is an useful concept to determine the similarity between signals (Oppenheim *et al*, 1997). Thus, in the first case (*correlation*) the similarity is 100%, whereas for the other cases (*cross-correlation*) it decreases to 85.3%, 80.6% and 76.1%. Fig. 7 shows the evolution of the climate external to the greenhouse (temperature and global solar radiation), control action and cost accumulation.

In order to evaluate the influence of meteorological factors into the performance of the approximated optimal control law simulations were carried out generating disturbances into the outside temperature and global solar radiation. In Fig. 5 is presented the evolution of the state variables. Fig. 7 and Fig. 9 show the external perturbations (external temperature and global solar radiation), control action (using the heater -positive control action- and percentage of opening window -negative control action), and the cost accumulation respectively. Fig. 8 shows the evolution of neural networks parameters and cost function performance. Finally, Fig. 6 shows the approximate optimal policy evaluation.

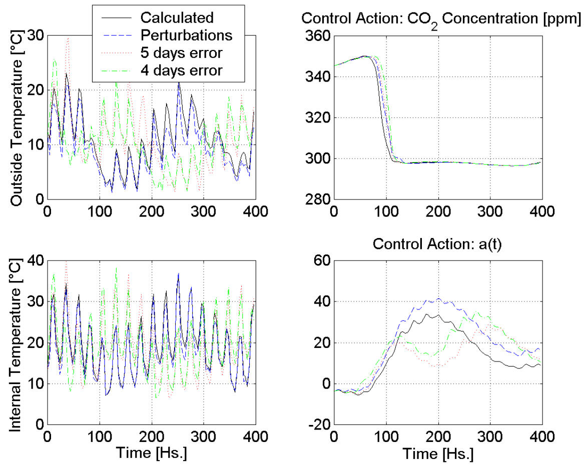

Fig. 7. Evolution of greenhouse variables, outside and inside temperatures, internal CO_2 concentration, Heater use (a(t)>0) and opening windows (a(t)<0).

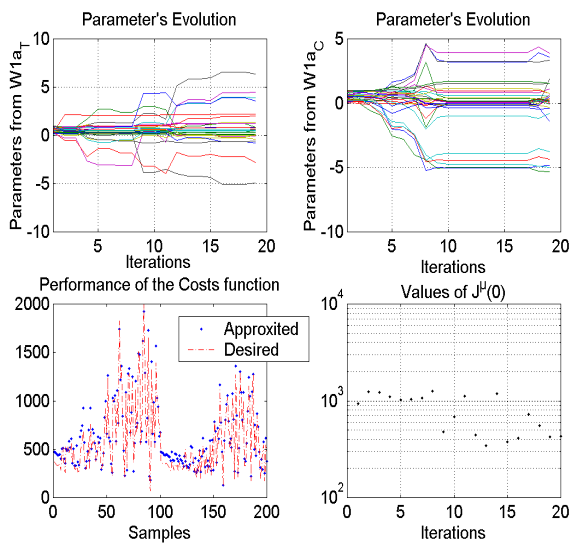

Fig. 8 Evolution of neural network parameters, cost function performance and values of $J^{\mu}(0)$.

5. COSTS EVALUATION

By observing the obtained numerical results of the on-line neurocontroller's performance under climatic conditions different from those were used in its calculation, the system's operative cost (Fig. 9) grows from \$7.18 to \$10, while the similarity degree among the conditions decrease (from 100%) to 76.1%.

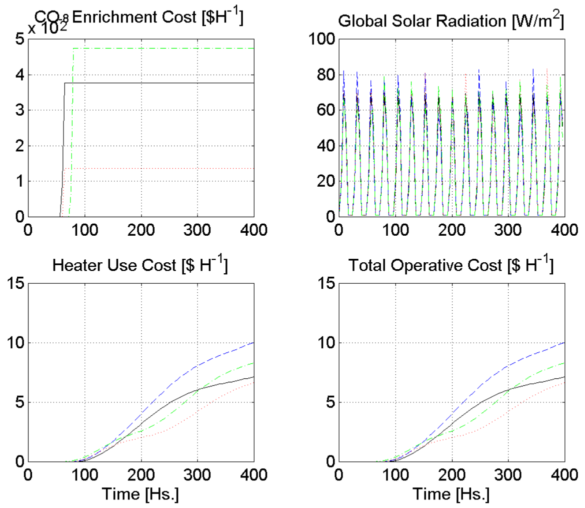

Fig. 9 Evolution of different cost factors: cost accumulation and global solar radiation.

6. CONCLUSIONS

A neuro-dynamic programming-based optimal controller for crop-greenhouse systems has been proposed. The obtained neurocontroller is suboptimal due to use of neural network for approximations. The neurocontroller is able to drive the crop-growth development minimizing a predefined performance index, which considers minimization of the greenhouse operative costs and the final state errors under physical constraints on process variables and actuator signals. In particular, it was applied to guide the tomato-seedling crop development through control of a greenhouse microclimate. In the neurocontroller design process nonlinear dynamic behavior of the crop-greenhouse system and the July climate data of 1999 of San Juan, Argentina, were considered. The obtained control law is suboptimal due to the use of neural networks to approximate both the optimal cost-to-go function and optimal policy. In order to show the practical feasibility and performance of the proposed neurocontroller, simulation studies were carried out for the tomato-seedling crop development, which would ease the transition to experimentations on a scale model of a greenhouse available in the Instituto de Automática's laboratory. Studies results shown that the cost accumulation tends to increase when do the forecast error (external temperature and solar radiation perturbations). The implementation of this control strategy for guiding the crop growth requires a low cost installation. The obtained control law is simple, and minimizes the operative costs involve along the control process evolution. Results from simulation shown a satisfactory control system performance of the tomato-seedling crop-greenhouse system.

7. REFERENCES

Bertsekas D. (1995). "Dynamic Programming and Optimal Control". Vols. I and II, Athena Scientific.

Bertsekas D. and J. Tsitsiklis. (1996). "Neuro-dynamic programming". Athena Scientific.

Bishop C. (1995). "Neural Networks for Pattern Recognition". University Press. Oxford.

Casti J. and R. Larson. (1978). "Principles of dynamic programming". Marcel Dekker, INC.

Fullana R. and C. Schugurensky. (1999). "Optimización de Sistemas Restringidos Utilizando Programación Dinámica Iterativa". Anales de la VIII RPIC, Mar del Plata.

Gutman P.O., Lindberg P.O., Ioslovich I. and I. Seginer. (1993). "A non-linear optimal greenhouse control problem solved by linear programming". J. Agric. Engng. Res. **55**, 335-351.

Hwang Y. And J. W. Jones. (1993). "Optimizing temperature and CO_2 in subtropical greenhouses". International Winter Meeting of the ASAE. Paper No. 93-3504.

Ioslovich I., Seginer I., Gutman P. O. and M. Borshchevsky. (1995). "Suboptimal CO_2 enrichment of greenhouses". J. Agric. Engng. Res., **60**, 117-136.

Jones, J. W. (1991). "Crop Growth, Development and Production Modeling". Proc. of the Symposium on Automated Agriculture for the 21st Century, ASAE 447-457.

Kirk. (1970). "Optimal Control Theory: An introduction". Prentice Hall.

Lapilli, S., R. Fullana, C. Schugurensky and J. Pucheta. (2001). "Modelo algebraico de temperatura de un invernadero. Algoritmos de control". IX RPIC, Santa Fe.

Lewis F. and L. Syrmos. (1995). "Optimal Control". John Wiley & Sons, Inc.

Nørgaard, M. (1997). "Neural Network Based System Identification Toolbox". Tech. Report. 97-E-851, Department of Automation, Technical University of Denmark.

Oppenheim A., Willsky A. and S. Hamid Nawab. (1997). "Signals and systems". 2nd edition by Prentice-Hall, Inc. Pg. 168-170.

Pucheta, J. A., C. Schugurensky, R. Fullana and S. Lapilli. (2001). "Optimización del costo operativo de un sistema cultivo-invernadero". IX Rpic. Santa Fe, Argentina.

Seginer I., Shina G., Albright L. D. and L. S. Marsh. (1991). "Optimal temperature set-points for greenhouse lettuces". J. Agric. Engng. Res. **49**, 209-226.

Seginer I. and R. W. McClendon. (1992). "Methods for optimal control of the greenhouse environment". *Transactions of the ASAE*. **35**, N° 4, 1299-1307.