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Review. Advantages and disadvantages of control theories applied in greenhouse climate control systems

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Abstract

Today agriculture is changing in response to the requirements of modern society, where ensuring food supply through practices such as water conservation, reduction of agrochemicals and the required planted surface, which guarantees high quality crops are in demand. Greenhouses have proven to be a reliable solution to achieve these goals; however, a greenhouse as a means for protected agriculture has the potential to lead to serious problems. The most of these are related to the inside greenhouse climate conditions where controlling the temperature and relative humidity (RH) are the main objectives of engineering. Achieving appropriate climate conditions to ensure high yield and quality crops reducing energy consumption have been the objective of investigations for some time. Different schemes in control theories have been applied in this field to solve the aforementioned problems. Therefore, the objective of this paper is to present a review of different control techniques applied in protected agriculture to manage greenhouse climate conditions, presenting advantages and disadvantages of developed control platforms in order to suggest a design methodology according to results obtained from different investigations.

Additional key words: controller; conventional control; optimal control; precision agriculture; protected agriculture.

Resumen

Revisión. Ventajas y desventajas de los sistemas de control climático aplicados en agricultura de precisión

Hoy en día la agricultura está cambiando de acuerdo a las necesidades de la nueva sociedad. Las nuevas tendencias son asegurar la producción de alimentos a través de prácticas tales como ahorro de agua, reducción en el uso de agroquímicos y el espacio requerido para sembrar los cultivos mientras se garantiza la alta calidad de los cultivos. Los invernaderos han demostrado ser una solución viable para garantizar estos objetivos. Sin embargo, el uso de un invernadero conlleva serios problemas. Los más importantes están relacionados con las condiciones del microclima dentro del invernadero, donde el objetivo de la ingeniería es controlar la temperatura y humedad relativa (RH). Alcanzar las condiciones adecuadas del microclima para garantizar la alta productividad y calidad de los cultivos mientras se reducen los consumos de energía ha sido el objetivo de diversos investigadores a través del tiempo. Diversos esquemas de teoría de control han sido aplicados con el objetivo de resolver los problemas antes mencionados. Por lo tanto, el objetivo de este artículo es presentar una revisión de las diferentes técnicas de control aplicadas en agricultura de precisión para manejar las condiciones del microclima del invernadero, presentando las ventajas y desventajas de los sistemas desarrollados con la finalidad de proponer una metodología de diseño de acuerdo a los resultados obtenidos de las diferentes investigaciones.

Palabras clave adicionales: agricultura de precisión; agricultura protegida; control óptimo; controlador; control convencional.

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Introduction

A greenhouse is an enclosed space that creates a different environment to that found outside due to the confinement of the air and to the absorption of short-wave solar radiation through a plastic or glass covers (El Ghoumari *et al.*, 2005). This generates a new environment inside the greenhouse which is better known as microclimate. The greenhouse microclimate can be manipulated by control actions, such as heating, ventilation, CO_2 enrichment to name a few; in order to provide appropriate environmental conditions (Bennis *et al.*, 2008). These modifications imply additional use of energy in the production process. Furthermore, it requires a control system that minimizes the energy consumption while keeping the state variables as close as possible to the optimum crop physiological reference (Coelho *et al.*, 2005). Horticulture in greenhouse conditions is a rapidly expanding interest and is consequently increasing in its economic and social importance.

Many efforts have been made to develop advanced computerized greenhouse climate control systems. In particular, interesting and important optimal control approaches have been proposed (Ioslovich *et al.*, 2009). As was previously reported, crop production using controlled environments has several advantages over conventional crop production such as greater productivity, better product quality, and low water and fertilizer consumption. Nevertheless, environmental requirements for living systems are very complex and nonlinear. Furthermore, the biological system likely has a significant and multiple effects on its physical surroundings (Pasgianos *et al.*, 2003). Researchers have used many control techniques in different fields. From the conventional or sometimes referred to as classic control theory such as: proportional, integral and derivative (PID) controllers, artificial intelligence (AI) such as fuzzy logic systems (FLS), artificial neural networks (ANNs) and genetic algorithms (GAs) to advanced techniques like predictive, adaptive, robust and non-linear control (Castañeda-Miranda *et al.*, 2006). The aforementioned control techniques have been widely utilized on research (Trabelsi *et al.*, 2007; Bennis *et al.*, 2008).

In this review, updated information is provided about modern methods to control the greenhouse environments which can be taken into account as criteria to design new greenhouse microclimate control systems. The paper is divided in four sections, the first focuses on the different control theories applied to design climate control systems for protected agriculture. The second section is an overview of the technology platforms where the controllers were implemented. The third section discuses new tendencies in the development of environmental controllers for protected agriculture. Finally, in the last section the conclusions are presented.

Control theories applied in greenhouse climate control systems: An analysis of advantages and disadvantages

Different research has been conducted regarding climate control for protected agriculture applications. The primary objective of these investigations is to find an accurate model that represents the greenhouse environmental dynamics and an efficient and flexible controller that adjusts the microclimate variables of

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Abbreviations used: AGA (annealing genetic algorithm); AI (artificial intelligence); ANN (artificial neural network); DIF (difference between average day temperature and average night temperature); DSP (digital signal processor); FL (feedback linearization); FLS (fuzzy logic system); FPGA (field programmable gate array);GA (genetic algorithm); MIMO (multiple-imput-multiple-output); MPC (model predictive control); PC (personal computer); PD (proportional derivative control); PDF (pseudo-derivative-feedback); PI (proportional integral control); PID (proportional integral and derivative control); PMP (pontryagin's maximum principle); PSO (particle swarm optimization); RH (relative humidity); SCS (sequential control search). Nomenclature: A_g (covered ground surface, m^{-2}); A_r (roof to soil rate, m^2 m^{-2}); C (greenhouse heat capacity, J K^{-1} m^{-2}); C_p (air specific heat, J K^{-1} kg^{-1}); e_i (internal mean vapour pressure, Pa); $e(t)$ (error); $E(s)$ (Laplace error representation); G (outside short-wave radiation, W m^{-2}); I_{LA} (leaf area index, m^2 m^{-2}); K_i (integral gain); K_d (derivative gain); $K_{out,air}$ (heat loss coefficient from greenhouse air to outside air); K_p (proportional gain); q_h (heat input, W m^{-2}); r_s (stomatic resistance, s m^{-1}); r_a (aerodynamic resistance, s m^{-1}); s (Laplace transform parameter); t (time, s); T_c (crop temperature, K); T_d (adjustment coefficient); T_G (internal air temperature, K); T_g (ground temperature, K); T_i (adjustment coefficient); T_o (external air temperature, K); T_r (roof temperature, K); $u(t)$ (process input); $U(s)$ (Laplace input representation); V_l (greenhouse air to soil area rate, m^3 m^{-2}); x_i (internal absolute humidity, kg m^{-1}); x_g (soil absolute humidity, kg m^{-3}); x_o (external absolute humidity, kg m^{-3}); $y(t)$ (process output); $y_d(t)$ (setpoint or desired process output); α_{ci} (convection heat transfer coefficient, W m^{-2}). Greek letters: γ (thermodynamic constant, Pa K); δ (leaf slope, Pa K); ϕ_v (ventilation rate, m^3 s^{-1}); η (radiation conversion factor); λ (water vaporization energy); ρ_a (air density, kg m^{-3}). Superscripts: * indicates that considered quantity is saturated at vapour pressure.

interest. This problem has been the focus of many researchers worldwide who have analyzed, experimented and proposed many climate control systems in order to manipulate variables such as temperature, relative humidity (RH), CO_2 enrichment, radiation and many others that are necessary to generate the fundamental conditions for successful protected agriculture.

Since most control theories require the mathematical model of the system for tuning and simulating the proposed algorithms, different greenhouse models have developed. It includes simple models that only describe air temperature to detailed models that even involve crop response. The traditional greenhouse climate models are based on energy and mass balances (Setiawan *et al.*, 2000).

A model based on aforementioned balances over an elementary volume of greenhouse air was proposed by Arvanitis *et al.* (2000). Here, air temperature is represented by a differential Eq. [1]:

$$\frac{dT_G}{dt} = \frac{1}{C}\left[K_{out,\,air}(T_o - T_G) + q_h \right] \qquad [1]$$

where the T_G is the greenhouse internal air temperature, C the greenhouse thermal capacity, $K_{out,\,air}$ is the heat loss coefficient from greenhouse air to outside air. T_o is the external air temperature and q_h is the heating power.

Recently, more detail models have been used for control proposes (Castañeda-Miranda *et al.*, 2006). Those models involve almost all variables that influence the greenhouse behavior.

$$C\frac{dT_G}{dt} = \\ = \eta G + \alpha_{ci}\left[A_r(T_r - T_G) + 2I_{LA}(T_c - T_G) + (T_g - T_G) \right] - \rho_a C_p (T_G - T_o) + q_h \qquad [2]$$

$$V_l \rho_a \frac{dx_i}{dt} = \\ = \frac{1}{\lambda}\left(\frac{2I_{LA}\rho_a C_p}{\gamma(rs+ra)}\left[\delta^*(T_c - T_G) + (e_i^* - e_i) \right] + \alpha_{ci}\frac{\lambda}{C_p}(x_g^* - x_i) \right) - \frac{\phi_v}{A_g}\rho_a (x_i - x_o) \qquad [3]$$

In Eqs. [2] and [3], T_c is the crop temperature, T_g is the ground temperature, T_r is the roof temperature, x_i is the internal absolute humidity, x_o is the external absolute humidity, x_g is the soil absolute humidity, e_i is the internal mean vapour pressure, C_p is the air specific heat, V_l is the greenhouse air to soil area rate, A_g is the covered ground surface, A_r is the roof to soil rate, r_s is the stomatic resistance, r_a is the aerodynamic resistance, G is the outside short-wave radiation, I_{LA} is the leaf area index, α_{ci} is the convection heat transfer coefficient, δ is the leaf slope, ρ_a is the air density, λ is the water vaporization energy, η is the radiation conversion factor, γ is the thermodynamic constant, ϕ_v is the ventilation rate and t is the time in s. The superscript * indicates that consider quantity is at saturated vapour pressure.

Finally, models that consider greenhouse-crop interaction and complex processes such as photosynthesis or transpiration have been developed (Van Straten *et al.*, 2000). By this way, the greenhouse system can be represented concisely in a space state form as:

$$\dot{x}_g = f_g\left\{ q_{gm}\left\{x_g, u_m, u_a\right\}, q_{ga}\left\{x_g, u_m, u_a\right\}, q_{gb}\left\{x_g, x_b, u_m\right\}, q_{gc}\left\{x_g, x_c, u_a\right\} \right\} \qquad [4]$$

$$\dot{x}_b = f_b\left\{ q_{gb}\left\{x_g, x_b, u_m\right\} \right\} \qquad [5]$$

$$\dot{x}_c = f_c\left\{ q_{gc}\left\{x_g, x_c, u_a\right\}, q_{cc}\left\{x_g, x_c\right\} \right\} \qquad [6]$$

Here, $f\{\}$s represent vector functions of the argument between brackets; x_g, x_b, x_c are the state vector of the greenhouse (g), the storage buffers (non-structural biomas) (b) and the crop (c*)*, respectively; u_m, u_a, the vectors of the manipulated control (m) and ambient (a) inputs, respectively; q_{ga}, q_{gm}, flux vectors representing fluxes between the greenhouse and the ambient environment (ga) and the operating equipment (gm), respectively; q_{gb}, q_{gc}, fluxes between greenhouse and buffer (gb) and between greenhouse environment and crop (gc), respectively; q_{cc}, flux vectors related to the internal greenhouse conditions x_g and the crop states x_c, but not directly on the ambient conditions outside the greenhouse. The state list typically consist of temperature, moisture content and carbon dioxide for greenhouse atmosphere, temperatures for the storage buffers, and various crop biomass states for the plans in the greenhouse.

It is easy to find how models have been improved in response to production schemes that require more precisely methods to control the environment greenhouse.

In this section, an analysis and classification of the different control theories is presented. Establishing a division between the controllers presented in current literature is complicated, due to the variety and integration of diverse techniques used to solve the same problem. Fig. 1 shows a classification proposed dividing

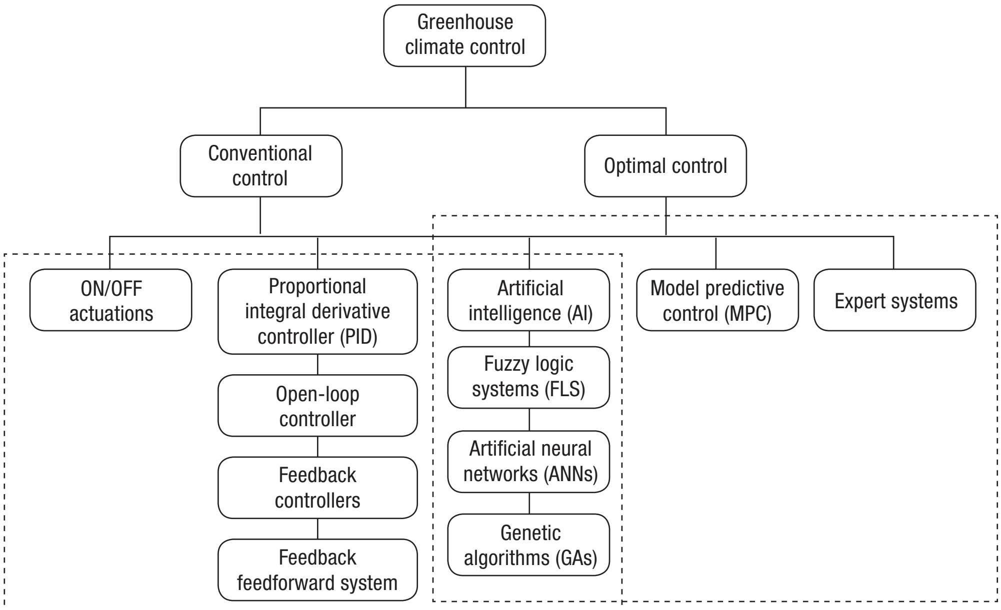

Figure 1. Greenhouse control theories classification.

greenhouse climate control task in two main fields. The first one is usually called conventional control which consists on control theories which try to control the greenhouse environment just by reducing the deviation between set points of the interest variables and measured values to zero. As examples of conventional control there are ON/OFF, PID, other classical controllers and also paradigms of AI such as ANNs, FLS, GAs, among others. The other field is optimal control, in which the requirement is to consider aspects such as greenhouse behavior, actuator capabilities, energy consumption and mainly crop response as input parameters of the control process. Here, Expert systems and Model Predictive Control (MPC) are the most common techniques. However, aforementioned AI-based techniques can be also considered as optimal control when they consider input parameters such as crop responses among others.

Conventional greenhouse climate control

The most representative component of this theory is the PID (Ang *et al.*, 2005); which is a feedback mechanism commonly used in industrial control systems (Fig. 2). Therefore, it is necessary to explain each component and action of the PID controller.

— Proportional (P) control: In certain cases having a smooth control and an error that is almost zero in the steady state is desired, where the proportional controller is suitable for this type of plant since that a proportional controller provides a control signal that is proportional to the error, that is, it returns its input multiplied by the proportional gain (K_p), thus, the control signal is given as:

$$u(t) = K_p e(t) \qquad [7]$$

$$e(t) = y_d(t) - y(t) \qquad [8]$$

and the transfer function is obtained by means of the Laplace transform as:

$$\frac{U(s)}{E(s)} = K_p \qquad [9]$$

— Integral action: When an integral action is implemented, the integral of the error is added to the control signal. If the error signal is large, then the control signal increases quickly, but if the error signal is small then the control signal increases slowly. It is remarkable that if the error approaches zero then the controller output would remain constant. Due to this feature, integral action can be used when a constant load is present in the plant; even when no error is present, the controller will keep on providing an output signal for compensation.

— Proportional integral (PI) control: Since a proportional control is not capable of compensating a load in the plant without error, the integral action is neces-

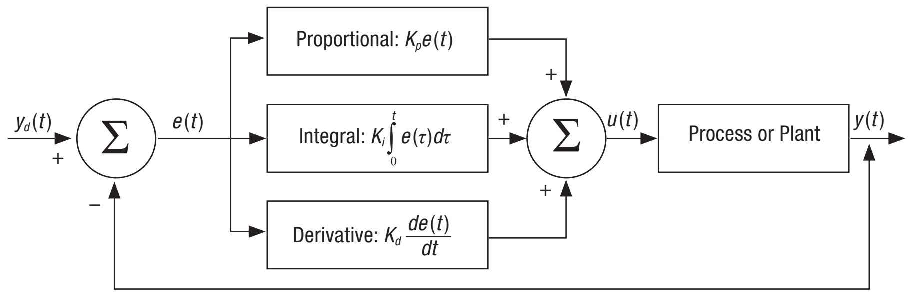

Figure 2. Block diagram of general PID controller.

sary. Integral action can compensate and provide a zero error; the PI controller is given as:

$$u(t) = K_pe(t) + K_i\int e(t)dt = K_p\left[e(t) + \frac{1}{T_i}\int e(t)dt\right] \quad [10]$$

where T_i adjusts the integral action and K_p adjusts both the integral and proportional actions. Its transfer function is given as:

$$\frac{U(s)}{E(s)} = K_p + \frac{K_i}{s} = \frac{K_ps + K_i}{s} = \frac{K_p(T_is+1)}{T_is} \quad [11]$$

$$T_i = \frac{K_p}{K_i} \quad [12]$$

— Proportional derivative (PD) control: The goal of a derivative controller is to provide a signal proportional to the signal error change rate, causing derivative action to be present only when there is a change in the error signal. In other words, the derivative action introduces damping to the system. The PD controller is given as:

$$u(t) = K_pe(t) + K_d\frac{de(t)}{dt} = K_p\left[e(t) + T_d\frac{de(t)}{dt}\right] \quad [13]$$

and whose transfer function is:

$$\frac{U(s)}{E(s)} = K_p + K_ds = K_p(T_ds+1) \quad [14]$$

$$T_d = \frac{K_d}{K_p} \quad [15]$$

— Proportional integral derivative (PID) control. By combining the three different control actions a PID controller is obtained by:

$$u(t) = K_pe(t) + K_i\int e(t)dt + K_d\frac{de(t)}{dt} \quad [16]$$

and whose transfer function is:

$$\frac{U(s)}{E(s)} = K_p\left(1 + \frac{1}{T_is} + T_ds\right) = K_p\left(\frac{T_iT_ds^2 + T_is + 1}{T_is}\right) \quad [17]$$

The PID controller is the most complete controller available and the most resorted to since it provides a quick response, a control signal that tends to provide stability to the system and a minimum steady state error. The PID controller is an important control tool for industrial processes and only three gains have to be tuned (Ogata, 2003; Dorf & Bishop, 2005).

Although the PID is the most utilized controller in industry and it is widely accepted for agricultural applications, it is not the only solution for agricultural problems. Occasionally it is not a good choice due to the absence of a reliable mathematical model within the system. Taking this into account, a climate control system based in ON/OFF operation has been proposed when the mathematical model is unknown, and this complicates the tuning of the controllers. It manages the times when actuators are turned on, and prevents external climatic changes issues based on recorded data (Ali & Abdalla, 1993). The aforementioned technique was studied by Hooper & Davis (1988), who implemented a controller based in an algorithm that modifies the greenhouse heating setpoints depending on previously achieved temperatures. This technique has shown good performance managing deviations in the setpoints through soft changes. Hooper (1988) also presented an integral greenhouse climate control by applying a mixture of controllers, a PI controller applied in heating and ventilation, and ON/OFF control applied for irrigation, pH, electrical conductivity and nutrients management. However, Setiawan *et al.* (2000) reported that a Pseudo-Derivative-Feedback (PDF) control presents better performance than a PI for agricultural application, due to the fact that PDF controls have better load handling capability than PI controls. PDF control was better than PI for systems without time delay and significantly better for systems with time delay.

It is easy to find current investigative work regarding the field of greenhouse microclimate control; however, reported results reveal that aforementioned techniques are not the most adequate to solve the problems inherent in greenhouses. The reason lies in the fact that the model of a greenhouse is very complex and it has many non-linearities; consequently, this has encouraged the development of new control techniques that do not require the greenhouse mathematical model (Sigrimis *et al.*, 2002).

In the past, the application of new and advanced techniques for control was limited because of the limited computational power that was then available. Controllers based on FLS, ANNs or GAs could not be implemented in the former technological platforms due to their high complexity. These unconventional techniques based on soft computing and computational intelligence are now gaining popularity in the field of agriculture. Several soft-computing, such as ANNs and knowledge-based systems have been implemented with significant success (Soto-Zarazua *et al.*, 2010).

FLS controllers are conceptually very simple; they consist of an input stage, a processing stage and an output stage. The first stage maps sensors and other inputs to the appropriate membership functions and truth values. The processing stage invokes the appropriate rules and generates a result for each. Finally, the output stage converts the combined results into a specific control output value. Furthermore, ANNs is a knowledge paradigm and automatic processing system that attempts to imitate how the nervous system of animals works. The principal advantage of this technique is that it does not require a model of the system. The system is composed of neurons with propagation, activation, and transfer functions that are interconnected among them in an effort to reduce the error to zero. GAs is a heuristic research that mimics the process of natural evolution. This heuristic is routinely utilized to generate solutions to optimization and search problems. GAs generate solutions to optimize problems using techniques inspired by natural evolution such as inheritance, mutation, selection and crossover.

The relatively new field of evolutionary computing has become increasingly popular in recent years due to the development of powerful and low-cost computational systems. Because AI based systems have been updated and improved, these techniques solve the main problem of classic controls that being the identification of the system which is commonly nonlinear (Caponetto *et al.*, 2002).

The classical solutions proposed are generally based on the linearization of the process behavior regarding the operating points. Other research has been carried out on this technique of linearization, not only dealing with the operating points, but also by taking into consideration all the input-output space to obtain several local linear models. The major difficulty with this technique is the model transition. Indeed, many techniques of modeling and identification based on FLS are often used for these types of systems (Trabelsi *et al.*, 2007). Some controllers base their operation on the aforementioned paradigm, as proposed by Castañeda-Miranda *et al.* (2006) who implemented a FLS on a field programmable gate array (FPGA) to control the temperature of the greenhouse microclimate or Kurata & Eguchi (1990) who applied this theory in crop management for protected agriculture.

Other systems which are classified in AI techniques are knowledge-based systems, as the one proposed by Gauthier & Guay (1990) which manages the climate control and production. This system supports dynamic optimization and continuous greenhouse monitoring. The proposed prototype was designed using object-oriented programming, obtaining good performance in the problem area. These expert-systems have proven to be a reliable alternative in greenhouse control applications. Jacobson *et al.* (1989) reported an expert system to control misting. This system was based on a strategy of an experienced grower. Gauthier (1992) reported changes to this scheme in a system that supports various types of digital process controllers as well as the creation and deployment of knowledge based control strategies with the goal of being able to intervene in a wide number of areas such as crop protection, climate control, crop nutrition, operational and strategic planning. This scheme received additional improvements such as changing the heuristic knowledge of the growers for data routinely collected in a commercial greenhouse (Seginer *et al.*, 1996).

Fuzzy systems achieved important results in the field of climate control for protected agriculture. Moreover, it is necessary to have reliable information of the system behavior, and that is not sufficient with this requirement a correct abstraction to create rules based in heuristic and empiric knowledge of the grower's experience is also necessary.

ANNs have proven their strengths and flexibility to adapt to non-linearities and unexpected parameters of the system. Their main disadvantage is that their proper training requires large multi-dimensional sets of data to reduce the risk of extrapolation and the uncertainty about their response to inputs which differ in relation to the training information. Therefore, minimizing the dimensionality of the problem, both input and state vectors become of paramount importance (Seginer, 1997).

GAs as FLS and ANNs offer the ability to control the system with a good performance without the requirement to base their operation on plant identification of the system. Although GAs represents a solution in the control of nonlinear systems, the computational requirements have limited its use *in situ* applications until recently. The final conclusion is that the use of AI based systems is justified in control problems where the system plant is highly nonlinear or when the model is not reliable or has not been identified.

Each control technique offers solutions for specific problems. Unfortunately, a specific controller that deals with the different characteristics and limitations presented in highly non-linear and complex systems of greenhouse microclimate has not yet been found. Consequently, hybrid models which combine different control schemes have begun to appear.

Combinations of classical control theory with AI and considerations of crop process have been demonstrated as promising. A demonstration of this was reported by Pinon *et al.* (2005); he proposed a scheme for greenhouse temperature control using the advantages of combining Feedback Linearization (FL) and standard linear MPC. The discussed hybrid control structure, MPC + FL, offers a reliable solution of nonlinear control problems, transforming a non-linear greenhouse system subject to input constraints, to an optimized problem for a linear greenhouse system.

Optimal control

The advantages of using optimal instead of conventional greenhouse climate control can be summarized as follows. An optimal control approach to greenhouse climate control fully exploits scientific quantitative knowledge concerning the greenhouse, the greenhouse equipment and the crop, captured all in a mathematical dynamic model that deals with the problem of maximizing the profit, achieving welfare of the crop through practices that minimizes production costs (Van Straten *et al.*, 2011).

In this section, climate controllers based on complex algorithms are discussed. An analysis of MPC, real time controllers, robust and non-linear control, feedforward and systems that take into consideration decision support tools to gain efficient temperature integration are presented. Also, a survey of reported methods that considers morphological and physiological characteristics of the crops is presented.

The need of guarantee yield and quality of greenhouse crops has demanded stricter control of plant climate; previously, controllers were utilized for the sole purpose of adjusting the microclimate variables, but with recently increasing costs of energy, an appropriate controller that also considers the energy consumptions is necessary. One example of this was reported by Nielsen (1995) who presented a computer algorithm design to distribute the energy demands of greenhouses, reducing the peaks presented in the actuator in the day-to-night and night-to-day transitions. Other authors, proposed more complex systems (Arvanitis *et al.*, 2000; Davis & Hooper, 2002). These methods operate by considering that greenhouse parameters vary with operating conditions and applied a new pole-placement scheme. It estimates the unknown parameters of the greenhouse on-line from sequential data of the greenhouse temperature and the heating power which is recursively updated to obtain a slightly soft control.

Sigrimis & Rerras (1996) reported a controller based on a linear model structure to track and predict greenhouse behavior as a Multiple-Input-Multiple-Output (MIMO) system. This method takes into consideration disturbances like uncontrollable inputs. Climate controllers systems have been improved in order to consider external disturbances and have the ability to compensate for them; even they take into account plant responses such as crop growth. Reports regarding feedforward controllers indicate that they are reliable and achieve good performance for greenhouse heating (Jewett & Short, 1992; Takakura *et al.*, 1994). On the other hand, real time systems have also been utilized in greenhouse applications, improving the systems to the point where operator intervention is only required to define the constraints of the heating setpoints.

Another real-time control algorithm for generating optimal heating setpoints was presented by Chalabi *et al.* (1996). This method adjusts greenhouse temperature setpoints over a period of time to achieve energy savings for a tomato crop, justifying these control actions by using the results of physiological studies showing that for some crops it is sufficient to maintain an average temperature in a greenhouse over a given period (Hurd & Graves, 1983; De Koning, 1990). The algorithm is based on a model of greenhouse energy requirements and on a numerical method for optimization, where the optimal control problem is converted into a non-linear programming problem solved by sequential quadratic programming.

AI was also applied combined with crop process knowledge to generate paradigms applied in protected agriculture. Fitz-Rodriguez & Giacomelli (2009) made use of FLS combined with ANNs to propose a better control strategy for agriculture under greenhouse conditions taking into account models of crop growth. However, one disadvantage of ANNs is that, it requires getting a considerable set of data to train the net. This problem was addressed by Linker *et al.* (1998) using previously acquired data over a two-month period in a commercial greenhouse to train the net. The resulting model not only fit with data, it also seemed qualitatively correct and produced reasonable optimization results in a scheme of CO_2 enrichment control.

Hybrid controllers which fuse FLS and GAs were presented by Goggos & King (2000) in a research project that applies qualitative reasoning and evolutionary computing in the design of optimal set points and control strategies for greenhouses. This fusion of different intelligent control techniques was also applied in an intelligent environment control for plant production systems. The author used a decision-marking system based on ANNs and GAs in order to optimize plant growth under hydroponics conditions and also identified the response of plant growth to the nutrient concentration (Hashimoto *et al.*, 2002).

One of the main problems with climate control is the greenhouse dynamic model which is highly non-linear. Consequently, many researchers have applied simplified models for the non-linear problem, such as Ioslovich *et al.* (1996), who designed a controller based on a simplified model of the crop growth with constraints on the control signals. The objective of this optimization was to take into account the cost of energy used by heating and ventilation systems.

When it is necessary to control non-linear systems where the plant model is unknown, the use of feedback-feedforward control is an alternative. In this configuration, unexpected events are considered in the control model and the controller attempts to reduce the error to zero no matter the disturbances. These system characteristics were used to design a non-linear controller for coupled air temperature and humidity (Albright *et al.*, 2002). A feedback-feedforward combination was also used by Pasgianos *et al.* (2003) in a system linearization and decoupling of a greenhouse, maintaining control of ventilation/cooling and moisture. This technique also served to compensate for external disturbances. Finally, the controller was designed to consider the actuators capabilities and saturation setpoints.

In this section, applied strategies in climate controller systems with the objective of saving energy are considered. Nevertheless control techniques that consider physiological plant processes are also studied and described in this section.

Horticultural research has indicated that for the majority of plants, crop growth responds to long-term average temperatures rather than specific day and night temperature profiles (Langhans *et al.*, 1980; Miller *et al.*, 1985). Based on this research it has been suggested that the heating set-point can be adjusted to ensure that a desired average temperature over a given period can be achieved and thereby energy savings obtained. This knowledge was applied by Sigrimis & King (2000) in the design of a tool available to exploit the interaction between photosynthesis and growth according to the intuition of the grower because this interaction is not well known for most plants. The method is based on varying heating set-points using previously recorded information in order to achieve the desired average for any user-defined period. The proposed system does not require weather information and the grower can also set safety limits as the ultimate minimum and maximum temperatures permitted.

These control schemes were exploited by authors like Gauthier *et al.* (1995), who presented control strategies applied in heat, cool and dry greenhouse air, and also in the regulation of CO_2, light and irrigation. Considering that plant processes vary with the day and vegetative state of the plant, they do not require strict control of the microclimate all the time. With this in mind, temperature integration systems for greenhouse cultivation were developed by Körner & Challa (2003a). The concept considers different crop processes, and a decoupled process with fast temperature response (*e.g.* photosynthesis or stress) from a process with a slow response time. The objective was to improve the temperature integration concept by introducing dynamic temperature constrains; these flexible boundaries depend on the underlying crop process while increasing the potential for energy saving in greenhouses.

A different approach was proposed with a decision support tool that assists in choosing the most appropriate climate according to the week of the year in order to obtain the optimal gains of sustainability and plant quality. The greenhouse climate and crop model are studied separately and jointly considering the effects of six different regimes with increasing degrees of freedom for various climate variables (Körner & Van Straten, 2008) which include: crop model, temperature integration, dynamic humidity control and negative DIF regimes (DIF = the difference between average day temperature and average night temperature, and therefore reduces the use of chemical growth regulators).

MPC is an advanced control technique applied in the field of protected agriculture. The objective was to predict the greenhouse variables behavior. Developments in MPC algorithms for greenhouse operation which takes into account weather predictions to generate new optimal control problems for each update of forecasted weather information as solved numerically by linear programming were also developed (Gutman *et al.*, 1993). A contribution to this scheme was offered by Van Straten *et al.* (2000) where information about crop growth simplifies the design of greenhouse control strategies to obtain a truly economical control strategy. This approach leads to the concept of selecting processes by time response where the short-term effects like photosynthesis and evapo-transpiration are dealt with by an automated model-predictive optimal controller, while the long-term effects are left to the grower.

Aiming energy saving proposes, MPC algorithm has seen advances that take into account constraints in both manipulated and controlled variables, using on-line linearization for a real-time application. This proposal was applied in greenhouse temperature regulation, achieving good performance and energy savings. The results were compared with a PID solution. MPC based controllers solve the problems commonly presented in PID systems (El Ghoumari *et al.*, 2005). Due to the advantages presented by MPC, different strategies have been applied to design optimal MPC controllers. The Particle Swarm Optimization (PSO) was applied to design a model-based predictive greenhouse air temperature controller subject to restrictions; the model employs data from the climate inside and outside the greenhouse, as well as the control inputs and controller outputs. The operation principle ensures set-point tracking and minimizes control efforts. The conclusions presented show better efficiency over GAs and sequential quadratic programming methods (Coelho *et al.*, 2005).

MPC with GAs facilitating the incorporation of energy and water consumption to adjust non-linear models parameters have been suggested. The combination of MPC and GAs permits the control of the greenhouse microclimate while achieving energy and water savings (Blasco *et al.*, 2007). GAs in annealing form (AGAs) has also been applied for calibrating classical controllers such as PID, where the AGAs play a role in the parameter identification, demonstrating advantages over traditional GAs like premature convergence and low computing efficiency that are required to implemented these (Fan & Zuo-hua, 2006). Feed-forward neural networks have been applied in conjunction with simple neural models to drive the system outputs to desired values (Fourati & Chtourou, 2007).

Robust control also contributed to systems in protected agriculture because of its ability to deal with uncertain parameters, disturbances or modeling errors. It was applied focusing on managing the high correlations between air temperature and hygrometry (Bennis *et al.*, 2008). Different methods have been applied attempting to find a reliable optimal control solution for greenhouse environment, utilizing concepts from advance sequential control search (SCS) or Pontryagin's maximum principle (PMP)(Seginer & McClendon, 1992), to systems that consider the crop model and its effects on greenhouse behavior (Jones *et al.,* 1990). The objective of these approaches was to include weather and greenhouse-crop characteristics such as ventilation and stomatal resistance in the control actions (Baptista *et al.*, 2010). Humidity control regimes were also proposed by using information about the vegetative state of the plant (Körner & Challa, 2003b).

Authors worldwide have dedicated time and substantial effort to develop not only control systems, but they have also been working to create strategies to ensure reliable measurements through the use of filters and signal processing techniques to guarantee good performance of controller systems (Ibrahim & Sørensen, 2010).

One of the main objectives of the aforementioned developments is energy savings; however, all require knowledge of plant processes which is limited and usually empiric or heuristic. Consequently, advanced smart sensors are being developed in order to measure crop specific characteristics such as plant transpiration dynamics and photosynthesis in order to understand how physiological processes occur in the plants and how they affect and modify their surroundings (Millan-Almaraz *et al.*, 2010).

Throughout this review, special attention has been directed to demonstrate that not only the controller is necessary to guarantee appropriate microclimate conditions, but a fundamental part of the design is the use of reliable systems which take into consideration the importance of failure detection tools. By applying a hybrid of physical/neural network models with robust failure detection, failures are correctly detected and identified, leading to a significant reduction of losses caused by failures (Linker *et al.*, 2000).

Technological platforms applied on climate control theories implementation

Technological platforms are also important when a system is being developed to solve specific problems; protected agriculture is not an exception to this rule. Agronomy field imposed hard operating conditions and found it is necessary to strictly consider these restrictions. Despite the fact that greenhouse climate is not a fast response system, robust platforms that guarantee uninterrupted operation are required, flexibility is crucial to improve changes in the system in order to solve emerging needs and lower cost is also necessary to ensure success of a newly emerging crop production industry (Fang & Zhen-xiao, 2008).

The first and most popular platform chosen for greenhouse control applications has been the personal computer (PC). The use of PCs in greenhouse operations has created possibilities to implement complex algorithms that were impossible to apply in the past (Fang & Zhen-xiao, 2008). Consequently, the integration of new task modules, sensor and communication devices becomes easier (Ali & Abdalla, 1993). Different conFigurations of PCs and networks have been proposed to achieve more efficient greenhouse management (Hooper, 1988).

Commercial climate control computers and proprietary data-logger were also applied (Nielsen, 1995; Linker *et al.*, 1998). These systems offer solutions for protected agriculture problems. However, PCs are not the most appropriate platforms for heavy duty field applications, and are characterized to be a noisy and harsh environment with high humidity rates that are subject to constant temperature changes. Consequently, PCs are susceptible to failures and damage caused by the greenhouse harsh environment. Another consideration when discussing the use of PCs is the high cost to integrate PC networks or property systems. Other technological platforms should be proposed to ensure reliable sustainability. Microcontroller and Digital Signal Processors (DSP) based systems have attempted to solve the aforementioned problems with promising results; however, their limited capacities have proven to be difficult in the application of advanced algorithms with considerable computational demands (Coelho *et al.*, 2005).

The development of embedded systems for a particular application has been demonstrated to be the best choice for industrial applications. This idea was translated into precision agriculture field, designing platforms that consider hardware requirements and the conditions where the system will be placed to ensure robustness in the operation and low cost for the developed embedded platform. Field Programmable Gate Arrays (FPGAs) have been demonstrated to be a solution with a high performance, flexibility and robustness for greenhouse embedded applications (Castañeda-Miranda *et al.*, 2006).

New tendencies on greenhouse climate control systems

This review clearly shows that there is a tendency to utilize climate controllers for protected agriculture applications where these are based on very simple control theories, like ON/OFF, PID controllers or some variation thereof. This tendency has been caused by the low computational power availability in the past. Consequently, the control was limited to basic operations and real-time processing was unreachable because of the absence of adequate processing devices. Because of this, recent mathematical algorithms and control theories evolved faster than computing technologies. Consequently, complex algorithms were not available to be implemented in any technological platforms at affordable cost a few years ago.

This scenario changed when computers cost decreased and the processing capabilities became considerably higher, at least to the point to make it possible to implement complex algorithms. Soon thereafter, modern control theories based on real-time control process, adaptive schemes or intelligent techniques were applied in order to achieve a more accurate, efficient and strict manipulation of the interest greenhouse variables. Considerations regarding quality, yield, water and energy savings were also studied and integrated in the control models (Vazquez-Cruz *et al.*, 2010). These low cost platforms also make it possible to design and implement sensor networks, mobile robots for agricultural proposes, image processing for early diseases and pest detection as well as many other contributions to agriculture (Sigrimis *et al.*, 2000; Contreras-Medina *et al.*, 2009).

Despite the excellent results obtained with the high performances low cost computers, and advanced algorithms, tendencies are changing again; recently investigations and reports lead to the development of controllers which also consider plant physiology and morphology. Phenomena such as transpiration and photosynthesis have been studied for better understanding of plant behaviors in order to control climatic and nutritional requirements, according with real plant needs. New energy savings strategies have been proposed considering the available information regarding plant processes, manipulating climatic conditions when it is necessary for plant growth and the establishment of adaptive operating ranges for actuators with more degrees of freedom where strategies are helpful and when the reduction of energy consumption is essential. Nevertheless, the information about plant processes is limited. More investigation is necessary to establish correlations between physiological processes and plant growth in regards to temperature, humidity, nutrition and others controllable variables of the greenhouse, with the objective of reaching a sustainable protected agriculture industry (Millan-Almaraz *et al.*, 2009).

Conclusions

Greenhouse climate control is currently one of the main objectives of engineering in precision agriculture. Temperature and humidity are variables which have a direct relationship with the plant production. Moreover, recent investigations have shown that is not enough to adjust temperature and humidity ratings to maximum and minimum setpoints which are affordable for plant needs. Because of this, many control theories have emerged along the years such as conventional control techniques and optimal control. Conventional control is based mainly on the proportional-integral-derivative controller and some variants. Furthermore, optimal control techniques relies mainly on AI algorithms and adaptive control theory which proposes an alternative way to solve the climate control problem when greenhouse mathematical model is unknown or often very complex. Another important fact which has limited the development of more advanced climate control system was the technological limitations a few years ago. However, the relatively new computational technologies such as microprocessors, digital signal processors and field programmable gate arrays are allowing continuing the implementation of more sophisticated control systems. According to some authors, the application of advanced controllers capable of following specific variable setpoints has not yet proven to be an optimal solution. Because of this, new tendencies are appearing in greenhouse climate control based on gathering extra information about physiological and morphological processes on the plant such and transpiration, stomata conductance and photosynthesis. These new control theories report that it is not necessary to have strict temperature and humidity set points. Instead of this, more flexible thresholds are proposed to save unnecessary energy consumption which is consumed when controller tries to follow the set point in a strict way. Phytocontrol is the new theory which proposes the use of the plant physiological responses as input sensor to establish the set point in the climate controller. Also, this has not proved to be a stable and reliable method, because it is necessary to gather a lot of information to prove the reliability of this. Nevertheless, different types of controllers have emerged demonstrating advantages and disadvantages between them, better performance for some actions among other characteristics. Researchers need to analyze different control theories to determine which one is the most proper for their projects according to their specific requirements of greenhouse climate control systems.

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References

Albright LD, Arvanitis KG, Drysdale AE, 2002. Environmental control for plants on earth and in space. Control Systems Magazine IEEE 21(5): 28-47.

Ali IA, Abdalla AM, 1993. A microcomputer-based system for all-year-round temperature control in greenhouses in dry arid lands. Comput Electron Agr 8(3): 195-210.

Ang KH, Chong G, Li Y, 2005. PID control system analysis, design, and technology. IEEE T Contr Syst T 13(4): 559-576.

Arvanitis KG, Paraskevopoulos PN, Vernardos AA, 2000. Multirate adaptive temperature control of greenhouses. Comput Electron Agr 26(3): 303-320.

Baptista FJ, Bailey BJ, Meneses JF, Navas LM, 2010. Greenhouses climate modelling. Tests, adaptation and validation of a dynamic climate model. Span J Agric Res 8(2): 285-298.

Bennis N, Duplaix J, Enéa G, Haloua M, Youlal H, 2008. Greenhouse climate modeling and robust control. Comput Electron Agr 61(2): 96-107.

Blasco X, Martínez M, Herrero JM, Ramos C, Sanchis J, 2007. Model-based predictive control of greenhouse climate for reducing energy and water consumption. Comput Electron Agr 55(1): 49-70.

Caponetto R, Fortuna L, Nunnari G, Occhipinti L, Xibilia MG, 2002. Soft computing for greenhouse climate control. IEEE T Fuzzy Syst 8(6): 753-760.

Castañeda-Miranda R, Ventura-Ramos E, Peniche-Vera RR, Herrera-Ruiz G, 2006. Fuzzy greenhouse climate control system based on a field programmable gate array. Biosyst Eng 94(2): 165-177.

Chalabi ZS, Bailey BJ, Wilkinson DJ, 1996. A real-time optimal control algorithm for greenhouse heating. Comput Electron Agr 15(1): 1-13.

Coelho JP, De Moura Oliveira PB, Boaventura Cunha J, 2005. Greenhouse air temperature predictive control using the particle swarm optimisation algorithm. Comput Electron Agr 49(3): 330-344.

Contreras-Medina LM, Torres-Pacheco I, Guevara-Gonzalez RG, Romero-Troncoso RJ, Terol-Villalobos IR, Osornio-Rios RA, 2009. Mathematical modeling tendencies in plant pathology. Afr J Biotechnol 8(25): 7391-7400.

Davis PF, Hooper AW, 2002. Improvement of greenhouse heating control. In: Control theory and applications, IEE Proceedings D 138, IET: 249-255.

De Baerdemaeker J, Munack A, Ramon H, Speckmann H, 2002. Mechatronic systems, communication, and control in precision agriculture. Control Systems Magazine, IEEE, 21(5): 48-70.

De Koning ANM, 1990. Long-term temperature integration of tomato. Growth and development under alternating temperature regimes. Sci Hortic 45(1-2): 117-127.

Dorf RC, Bishop RH, 2005. Sistemas de control moderno. Pearson Education, Madrid, 882 pp.

El Ghoumari MY, Tantau HJ, Serrano J, 2005. Non-linear constrained MPC: Real-time implementation of greenhouse air temperature control. Comput Electron Agr 49(3): 345-356.

Fan X, Zuo-Hua T, 2006. Application of a genetic simulated annealing algorithm in the greenhouse system. Computer Simulation 12: 045.

Fang L, Zhen-Xiao L, 2008. Research on the control mode of agriculture greenhouse control system in China. J Agr Mechaniz Res 10: 223-226.

Fitz-Rodríguez E, Giacomelli GA, 2009. Yield prediction and growth mode characterization of greenhouse tomatoes with neural networks and fuzzy logic. T ASABE 52(6): 2115-2128.

Fourati F, Chtourou M, 2007. A greenhouse control with feed-forward and recurrent neural networks. Simul Model Pract Th 15(8): 1016-1028.

Gauthier L, 1992. A smalltalk-based platform for greenhouse environment control. Part I. Modeling and managing the physical system. T ASABE 35(6): 2003-2009.

Gauthier L, Guay R, 1990. An object-oriented design for a greenhouse climate control system. T ASABE 33(3): 999-1004.

Gauthier L, De Halleux D, Boisvert A, Trigui M, Zehrouni A, 1995. A control strategy for the operation of a reversible heat-pump in greenhouses. Appl Eng Agr 11(6): 873-879.

Goggos V, King RE, 2000. Qualitative-evolutionary design of greenhouse environment control agents. Comput Electron Agr 26(3): 271-282.

Gutman PO, Lindberg PO, Ioslovich I, Seginer I, 1993. A non-linear optimal greenhouse control problem solved by linear programming. J Agr Eng Res 55(4): 335-351.

Hashimoto Y, Murase H, Morimoto T, Torii T, 2002. Intelligent systems for agriculture in Japan. IEEE Contr Syst Mag 21(5): 71-85.

Hooper AW, 1988. Computer control of the environment in greenhouses. Comput Electron Agr 3(1): 11-27.

Hooper AW, Davis PF, 1988. An algorithm for temperature compensation in a heated greenhouse. Comput Electron Agr 2(4): 251-262.

Hurd RG, Graves CJ, 1983. The influence of different temperature patterns having the same integral on the earliness and yield of tomatoes. III Int Symp on Energy in Protected Cultivation (ISHS) 148: 547-554.

Ibrahim IA, Sørensen CG, 2010. A more energy efficient controller for the greenhouses climate control system. Appl Eng Agr 25(3): 491-498.

Ioslovich I, Gutman P, Linker R, 2009. Hamilton-Jacobi-Bellman formalism for optimal climate control of greenhouse crop. Automatica 45(5): 1227-1231.

Ioslovich I, Gutman P, Seginer I, 1996: A non-linear optimal greenhouse control problem with heating and ventilation. Optim Contr Appl Met 17(3): 157-169.

Jacobson BK, Jones PH, Jones JW, Paramore JA, 1989. Real-time greenhouse monitoring and control with an expert system. Comput Electron Agr 3(4): 273-285.

Jewett TJ, Short TH, 1992. Computer control of a five-stage greenhouse shading system. T ASABE 35(2): 651-658.

Jones P, Jones JW, Hwang Y, 1990. Simulation for determining greenhouse temperature setpoints. T ASABE 33(5): 1722-1728.

Körner O, Challa H, 2003a. Design for an improved temperature integration concept in greenhouse cultivation. Comput Electron Agr 39(1): 39-59.

Körner O, Challa H, 2003b. Process-based humidity control regime for greenhouse crops. Comput Electron Agr 39(3): 173-192.

Körner O, Van Straten G, 2008. Decision support for dynamic greenhouse climate control strategies. Comput Electron Agr 60(1): 18-30.

Kurata K, Eguchi N, 1990. Machine learning of fuzzy rules for crop management in protected cultivation. T ASAE 33(4): 1360-1368.

Langhans RW, Wolfe M, Albright LD, 1980. Use of average night temperatures for plant growth for potential energy savings. Symposium on More Profitable Use of Energy in Protected Cultivation (ISHS) 115: 31-38.

Linker R, Seginer I, Gutman P, 1998. Optimal CO_2 control in a greenhouse modeled with neural networks. Comput Electron Agr 19(3): 289-310.

Linker R, Gutman PO, Seginer I, 2000. Robust model-based failure detection and identification in greenhouses. Comput Electron Agr 26(3): 255-270.

Millan-Almaraz J, Guevara-Gonzalez R, Romero-Troncoso R, Osornio-Rios R, Torres-Pacheco I, 2009. Advantages and disadvantages on photosynthesis measurement techniques: A review. Afr J Biotechnol 8(25): 8316-8331.

Millan-Almaraz J, Romero-Troncoso R, Guevara-Gonzalez R, Contreras-Medina L, Carrillo-Serrano R, Osornio-Rios R, Duarte-Galvan C, Rios-Alcaraz M, Torres-Pacheco I, 2010. FPGA-based fused smart sensor for real-time plant-transpiration dynamic estimation. Sensors 10(9): 7340-7349.

Miller WB, Albright LD, Langhans RW, 1985. Plant growth under averaged day/night temperatures. Symposium Greenhouse Climate and its Control (ISHS) 174: 313-320.

Nielsen OF, 1995. Climate computer algorithms for peak shaving of greenhouse heating demand. Comput Electron Agr 13(4): 315-335.

Ogata K, 2003. Ingenieria de control moderna. Pearson Education. Madrid, 894 pp.

Pasgianos GD, Arvanitis KG, Polycarpou P, Sigrimis N, 2003. A nonlinear feedback technique for greenhouse environmental control. Comput Electron Agr 40(1-3): 153-177.

Pinon S, Camacho EF, Kuchen B, Peña M, 2005. Constrained predictive control of a greenhouse. Comput Electron Agr 49(3): 317-329.

Seginer I, 1997. Some artificial neural network applications to greenhouse environmental control. Comput Electron Agr 18(2-3): 167-186.

Seginer I, McClendon RW, 1992. Methods for optimal control of the greenhouse environment. T ASAE 35(4): 1299-1307.

Seginer I, Hwang Y, Boulard T, Jones JW, 1996. Mimicking and expert greenhouse grower with a neural-net policy. T ASAE 39(1): 299-306.

Setiawan A, Albright LD, Phelan RM, 2000. Application of pseudo-derivative-feedback algorithm in greenhouse air temperature control. Comput Electron Agr 26(3): 283-302.

Sigrimis N, Rerras N, 1996. A linear model for greenhouse control. T ASABE 39(1): 253-261.

Sigrimis N, Anastasiou A, Rerras N, 2000. Energy saving in greenhouses using temperature integration: A simulation survey. Comput Electron Agr 26(3): 321-341.

Sigrimis N, Antsaklis P, Groumpos PP, 2002. Advances in control of agriculture and the environment. IEEE Contr Syst Mag 21(5): 8-12.

Sigrimis N, King RE, 2000. Advances in greenhouse environment control. Comput Electron Agr 26(3): 217-219.

Soto-Zarazua GM, Rico-Garcia E, Ocampo R, Guevara-Gonzalez RG, Herrera-Ruiz G, 2010. Fuzzy-logic-based feeder system for intensive tilapia production (*Oreochromis niloticus*). Aquacult Int 18(3): 379-391.

Takakura T, Manning TO, Giacomelli GA, Roberts WJ, 1994. Feedforward control for a floor heat greenhouse. T ASABE 37(3): 939-945.

Trabelsi A, Lafont F, Kamoun M, Enea G, 2007. Fuzzy identification of a greenhouse. Appl Soft Comput 7(3): 1092-1101.

Van Straten G, Challa H, Buwalda F, 2000. Towards user accepted optimal control of greenhouse climate. Comput Electron Agr 26(3): 221-238.

Van Straten G, Van Willigenburg LG, Van Henten EJ, Van Ooteghem RJC, 2011. Optimal control of greenhouse cultivation. CRC Press, NY, USA.

Vazquez-Cruz M, Torres-Pacheco I, Miranda-Lopez R, Cornejo-Perez O, Osornio-Ríos AR, Guevara-Gonzalez R, 2010. Potential of mathematical modeling in fruit quality. Afr J Biotechnol 9(3): 260-267.