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Environmental Control for

Plants on Earth and in Space

Plants have evolved with an ability to cope with the inconsistencies of weather and survive, but seldom, in nature, does an individual plant reach its genetic potential. Plant production within closed environments strives to bring each plant to near its genetic potential. Control of shoot and root environments has been a central feature of production systems, whether within plant growth chambers (or rooms), greenhouses, or totally closed environments such as envisioned by NASA for food production and waste treatment (bioregeneration) in space.

When a cover is interposed between plants and the natural (outdoor) environment, the environments of the plants are altered, sometimes drastically. Light and air velocity may be reduced. For example, air temperature may become less consistent from minute to minute but more consistent from day to day, and relative humidity and carbon dioxide concentration may become significantly higher or lower

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than ambient. Controlled environment plant production systems have evolved over the past decades to where indoor environments can be managed to be more or less independent of the natural environment.

Plant production systems have become more sophisticated. At one time, the focus of environment control was simply to maintain blueprint set points. The next step was to maintain set points determined to be optimal for the crop for that location and time of year. Recently, the goal has changed to maintaining set-point trajectories determined in real time, based on economic criteria. This last step is a current focus of research, and much work remains to make the possibilities real.

Climate control has changed over the past several decades from manual to digital operations, and control computers have become faster and more capable. Tools exist today to develop near-optimum control systems for plant production on earth and in space. When more than one or two state variables are involved, however, computations are still prohibitively expensive to be implemented in real time for truly optimal control. This has led to many efforts to develop simplified models and shortcuts that can be solved, and the associated systems controlled, in real time.

What follows focuses first on the environment control of plant production in commercial greenhouses and plant growth chambers and then contrasts that growing system with the needs for rather different control strategies to grow plants in space applications. To demonstrate key characteristics of greenhouse environment control, a nonlinear controller for coupled air temperature and humidity, with various methods of feedback and feedforward control appropriate for this system, is presented.

Hierarchical Decomposition of Greenhouse Climate Management

Industrial process control is often characterized by hierarchical control because of the many inherent complexities of the controlled systems. Plant culture can exhibit the same degree of complexity due to the many time scales of responses and the intimate involvement of a biological system. The environment, naturally, has many effects on the biological system, and the biological system has numerous effects on the enclosing environment.

The response time of a greenhouse exposed to the sun's sudden emergence from behind a cloud can be measured in seconds. The response time of a crop's mass development rate in response to a sudden change of carbon dioxide level in the air must be measured in days or perhaps weeks. In general, the physical systems of plant production respond quickly, whereas the biological systems respond relatively slowly (within reasonable limits, of course). Process variables may be classified as "fast" or "slow," but no reason exists to limit decomposition of the control system to only these categories. A four-level decomposition is shown in Table 1 (see [1], as adapted by [2] for greenhouses) and is a perspective frequently taken for greenhouse climate control.

Level 3 control can be assumed as a function of market considerations and is generally left to the discretion of the facility manager. Level 2 control is composed of biological considerations but should be the ultimate control considerations for the system, as driven by level 1 control. The interactions of control levels 1 and 2 lead to considerations of optimal control for energy and production cost management. The efficacy of level 1 control depends heavily on level 0, which can become a serious concern because of the large sizes of commercial greenhouse air spaces. Large commercial greenhouse operations are sized by the hectare, and the actions of level 0 control may not propagate throughout the system under control influence for many minutes.

Plant Requirements and Environment Needs

Climate control for commercial plant production comprises numerous criteria and constraints. Physical yield is usually an important consideration, but the ephemeral characteristic of "quality" can be equally critical. Crop timing is also highly important, particularly for floriculture products associated with holidays, but also for foliage and vegetable crops to meet production schedules and sales contracts. Production costs and risks must also be carefully considered. These five criteria may lead to conflicting control requirements. The conflict may be solvable within the planning horizon of the crop cycle but can also arise within the operational (control) planning horizon. As an example, control may be based on an evaluation of crop needs at the moment, solar availability, current outdoor air temperature, and the anticipated cost of heating fuel.

Optimization has been a consistent goal of climate control for commercial plant production. Optimization considerations are less critical when controlling plant growth chambers and rooms and are viewed with very different constraints when designing plant production control systems for space applications. Optimization may involve determining the best trajectory through a day or through an entire crop cycle.

Table 1. A four-level hierarchical decomposition of greenhouse climate management and control (from [2]).

Level	Controlled Parameter(s)	Relevant Time Scale
3	Production space and time	Growing season or year
2	Crop growth and production	Hours/days/weeks
1	Greenhouse climate	Minutes
0	Actuators (e.g., fans and valves)	Seconds

Temperature

Temperature control in greenhouses affects growth and development processes directly, as well as other processes such as nutrient uptake, disease resistance, and pest development and activity. The effect of temperature on development, however, is often greater than its effect on photosynthesis. Gross carbon assimilation by a plant canopy is only moderately affected by air temperature [3]. The effect is within perhaps 20% of the average over the air temperature range from 14 to 40 °C, with a peak near 30 °C. Photosynthesis, photorespiration, and maintenance respiration interact to create this effect. Maintenance respiration increases rapidly as air temperature rises above 30 °C, even at relatively high concentrations of carbon dioxide (e.g., $700\ \mu\text{mol}\cdot\text{mol}^{-1}$) and light levels (e.g., $2000\ \mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$).

The focus of environment control has changed to maintaining set-point trajectories determined in real time, based on economic criteria.

Air temperature affects development through promoting more rapid leaf expansion (and thereby thinner leaves). If the canopy has not closed, larger individual leaves intercept more light, and growth is faster. For example, in [4], Marsh found leaf expansion was sufficiently increased when air temperature was raised from 24 to 27 °C that light interception, photosynthesis, and thereby growth accelerated by approximately 5% in lettuce.

Root zone temperature is also a consideration for control because of its effect on development and perhaps growth. Many commercially important crops are propagated from vegetative cuttings. The cuttings are placed in soil or soil-less media and the root zone environment (temperature, dissolved oxygen) is maintained to promote cellular differentiation into root primordia. In general, warmer root zone temperature increases root initiation and development (up to approximately 30 °C).

Light

Light is the only source of energy for plant growth, and the major effect of light on plants is through photosynthesis. The growth rate of a closed plant canopy is closely related to photosynthesis and thereby photosynthetically active radiation (PAR). Light saturation is a condition where plant processes become noticeably less efficient in their use of the incident radiation, which occurs at relatively high light levels. Greenhouses often transmit little more than half of the solar radiation incident upon their exterior surfaces. Thus, light saturation is less likely to occur in greenhouses than outdoors. Before light saturation is significant, the photosynthetic response to light is relatively linear. Thus, one could expect growth rate to be approximately linear with respect to the daily light integral intercepted by the crop. Evidence of such linearity for lettuce is presented by Both in [5]. In [6], Cockshull presents data to show linearity of yield with respect to the accumulated light integral for tomato, and similar results have been presented by other authors.

Supplemental lighting for crop production is becoming more common. Various strategies of control are used. When daylight hours are short, the day may simply be extended. If the ambient light falls to very low levels, supplemental lights may be activated. Control to a consistent daily integral is less common; however, [7] presents a rule-based control algorithm that achieves such control without using weather predictions for the day (the accuracy of which can be problematic in many climate regions). Supplemental lights and movable shade systems are required to achieve a consistent daily light integral throughout the year.

Carbon Dioxide

Carbon dioxide enrichment as a means of enhancing plant growth is now well established. Concentrations up to three to five times ambient levels show advantage, but diminishing returns are seen at higher values. Furthermore, the actual benefits of carbon dioxide enrichment may be uneconomical when other factors (such as light level) are limiting.

Suggested concentration levels have been established for many crops, but the temporal dynamics of carbon dioxide assimilation are not yet well quantified. Response times to changes of aerial concentration are measured in significant fractions of an hour, thus typical set-point management is usually sufficient for control. However, the opportunity exists to determine the best set point in real time by evaluating the expected combination of light level, ventilation rate, crop characteristics, and carbon dioxide concentration (e.g., [8]).

Relative Humidity

The moist air (psychrometric) interactions of plant environments are complex, but fortunately there seem to be few detrimental effects of permitting relative humidity (or vapor pressure deficit) within an established plant canopy to vary over a wide range.

Low humidity (high vapor pressure deficit, e.g., in excess of 1-2 kPa) leads to reduced plant growth, presumably by causing stomata closure to conserve water. High humidity (low vapor pressure deficit, e.g., 0.3 kPa) can reduce transpiration, limit calcium uptake, induce physiologic disorders in some plant species, and promote fungal diseases and insect infestations. High relative humidity may also produce foliage and leafy vegetable crops that are unable to tolerate the drier environments (without dehydrating) in which they find themselves after leaving the greenhouse.

Air Movement

Excessive air movement through crop canopies leads to potential water stress and reduced growth. Too little air movement can lead to carbon dioxide depletion within the canopy, reduced transpiration, and disease problems associated with excess canopy moisture. However, this factor of the environment is typically a matter of design, not control, although opportunities exist to incorporate control. For example, air circulation and mixing fans could be activated at light levels above which carbon dioxide depletion within the canopy could be anticipated to occur or if moisture condensation on plants occurs.

Plant Responses to Their Environments

Time Constants of Biological Systems

Many time constants characterize biological processes. Long response times (e.g., greater than 24 hours) characterize crop development and distribution of assimilates within the plant, canopy and root development, and growth.

A common approach to controlling long response time dynamics is to use rule-based control (e.g., set points) and, if the criteria cannot be followed precisely, take advantage of the plant's ability to integrate its responses and respond to the average. Moreover, control "optimization" can be approached by adopting constraints and permitting the criteria to vary within the constraints, rather than demanding fixed set points. This can be beneficial in managing some production costs, such as energy use.

Processes with response times of less than a day (e.g., photosynthesis, nutrient transport, and transpiration) are generally not compensated over times greater than a day. Instead, control systems (not the grower's input) must be imposed.

Photosynthesis is a primary plant process. Carbon dioxide is converted first to nonstructural matter (e.g., sugars and starches) and then to structural matter (e.g., cellulose). In general, nonstructural dry mass production is much more sensitive to short-term variations of environmental conditions than is structural dry mass production. Ultimately, however, photosynthesis dynamics must depend on the dynamics of stomata opening and closing and the associated biochemical reactions. Evidence has shown that stomata change relatively slowly compared to temporal changes of greenhouse climate and the actions of environmental control equipment. Twenty minutes are often needed for stomata to adjust. Thus, from a building control viewpoint, the biological systems in a greenhouse or plant growth chamber/room can be considered to react in a quasi-steady-state manner.

Certain plant reactions must be addressed within a very short time period, particularly reactions to acute stress. Overheating, chilling, sudden loss of water in a hydroponic system, and sudden extreme solar irradiation can all cause damage within moments. Preferably, these upsets are prevented by good system design and need not be compensated by the associated control system.

Ability of Plants to Integrate

The two most important environmental parameters for plant growth are light and temperature. For plants, light is defined in terms of the photosyntheticphoton flux density (PPFD, $\mu mol \cdot m^{-2} \cdot s^{-1}$) within the wavelength band between 400 and 700 nm (termed PAR). Plants demonstrate a considerable ability to integrate each of these parameters and respond to the average. This ability has led to considerable work to define control methods that follow the optimal path of environmental conditions through a day to limit the cost of heating and, to a lesser extent, the cost of supplemental lighting.

Climate control for commercial plant production encompasses several criteria: physical yield, crop quality, and production costs and risks.

Dynamic Model Considerations in the Crop Production Process

Typical Constraints in Crop Models

Although the dynamics of plant growth can be separated from the dynamics of greenhouse climate control, plant needs impose constraints thereon. The three most common areas of constraints involve temperature, relative humidity, and carbon dioxide concentration.

Daily values of maximum and minimum air temperatures may be specified to avoid stress or plant damage. Root temperature may be specified to achieve proper plant development. Average day and night air temperatures may be specified to reach desired plant quality, growth, and timing.

Maximum carbon dioxide concentration may be a constraint imposed by human health and plant response. Some evidence exists that stomata begin to close when the carbon dioxide concentration is above perhaps 1500 to 2000 $\mu mol \cdot mol^{-1}$. Of course, human health may be affected if the concentration is significantly higher than 2000 $\mu mol \cdot mol^{-1}$. Furthermore, air leakage (or even limited ventilation) may impose constraints of venting carbon dioxide at a cost that outweighs the advantages.

Relative humidity (or equivalently, water vapor pressure) may be kept significantly below saturation to prevent condensation on canopies. Condensation can be caused by thermal radiation loss from the canopy to a cold structural cover, which reduces canopy temperature below air temperature and encourages plant diseases such as mildew and botrytis. High relative humidity is also detrimental because it suppresses transpiration and impairs flower pollination (as in tomatoes), as examples. At the other extreme, a lower limit may be desired to prevent water stress with concomitant closing of stomata and reduced photosynthesis.

General Form of a Greenhouse Model

Mathematically, plant state variables can be represented by the vector X_p in the first-order differential equation forms of [9]:

$$\frac{dX_p}{dt} = g\left(X_p, X_c, U_e\right) \tag{1}$$

and

$$\frac{dX_c}{dt} = f\left(X_c, X_p, U_e, U_c\right) \tag{2}$$

where $X_p =$ plant state variables (e.g., shoot biomass, root biomass, leaf area, nitrate concentration, fruit mass); X_c = climate state variables (e.g., air temperature, relative humidity, carbon dioxide concentration, air movement); U_e = external inputs (e.g., solar radiation, outdoor air temperature, outdoor relative humidity, outdoor carbon dioxide concentration); and U_c = control inputs (e.g., ventilation rate, heat flux, carbon dioxide flux, supplemental light intensity).

The research literature is replete with plant and crop growth models. The biological processes of growth and reproduction are complicated, and the published models frequently mirror a similar level of complexity. For example, a tomato model (TOMGRO) [10] contains 69 state variables, which far exceeds practical application for control. In [11], de Konig considers the tomato crop in even greater detail and includes more than 300 state variables. An interesting approach is to use these models to train artificial neural networks (ANNs) and then use the ANN in model-based control applications.

Greenhouses typically have limited thermal storage capacity. Thus, g in (1) has fast dynamics compared to f in (2), creating "stiff" differential equations. This permits climate control separate from plant dynamics or a quasi-static solution of the climate control problem. In contrast, the longer time constants of the biological system permit optimization with, perhaps, a daily time step in which climate control set points are established. However, the biological system model should contain few enough state variables that optimization is possible online. An example of such a simple model is the two-state variable model for lettuce, reported by van Henten [2], which is representative of two-state models for vegetative growth. In [12], Tap presents a reduction of the de Konig tomato model to a two-state variable problem. The model of van Henten is summarized briefly below as a representative example.

Assume that a leafy (nonreproductive) crop can be described by two dry mass states: structural and nonstructural. Structural dry mass represents structural components such as cell walls. Nonstructural dry mass is generally composed of mass in solution, such as glucose, sucrose, and starch.

The time rates of accumulation of these two masses can be expressed by

$$\frac{dX_n}{dt} = c_\alpha \phi_{\text{phot}} - r_{gr} X_s - \phi_{\text{resp}} - \frac{1-c_\beta}{c_\beta} r_{gr} X_s \tag{3}$$

and

$$\frac{dX_s}{dt} = r_{gr} X_s \tag{4}$$

where each mass accumulation rate is expressed in $\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$.

The term φ_{phot} is the gross carbon dioxide uptake due to photosynthesis of the canopy ($\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$), r_{gr} is the rate (in s^{-1}) at which nonstructural material is used for growth of structural material, and ϕ_{resp} is the maintenance respiration expressed as amount of carbohydrate that is used ($\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$) to maintain the life processes in the plant. The term c_α represents conversion of assimilated carbon dioxide into sugars (or equivalents), and c_β portrays respiratory and synthesis losses due to the conversion of carbohydrates into structural matter.

Gross photosynthesis may be modeled empirically (for example, [13]) through the following exponentially asymptotic form

$$\phi_{\text{phot}} = \phi_{\text{phot, max}}\left[1 - \exp\left(-c_k c_{\text{lar},s}(1-c_\tau)X_s\right)\right]. \tag{5}$$

The coefficient, $\phi_{\text{phot, max}}$, is defined as the gross carbon assimilation at the specific canopy condition of an effective surface area equal to the soil area. The geometry and optical properties of the canopy are accounted for by the exponential term of (5), where $c_{\text{lar},s}$ is the ratio of leaf area to shoot structural mass, $\text{m}^2\cdot\text{kg}^{-1}$. The extinction coefficient of the canopy is expressed by c_k, and the ratio of root dry mass to total crop dry mass is expressed by c_τ.

The gross carbon assimilation of the canopy is a function of light and carbon dioxide concentration in the ambient air and may be expressed as

$$\phi_{\text{phot, max}} = \frac{\varepsilon c_{\text{par}} c_{\text{rad},rf} V_i \sigma_{\text{CO}_2}(X_c - \Gamma)}{\varepsilon c_{\text{par}} c_{\text{rad},rf} V_i + \sigma_{\text{CO}_2}(X_c - \Gamma)} \tag{6}$$

where ε is the efficiency with which light is converted to dry mass ($\text{kg}\cdot\text{J}^{-1}$). The term c_{par} is the ratio of PAR to total (solar) radiation, c_{rad,r_f} is the averaged light transmission of the greenhouse structure (dimensionless), and V_i is the solar insolation outside the greenhouse ($\text{W}\cdot\text{m}^{-2}$). The canopy conductance for carbon dioxide movement into the leaves is σ_{CO_2} ($\text{m}\cdot\text{s}^{-1}$) and X_c is the carbon dioxide concentration in

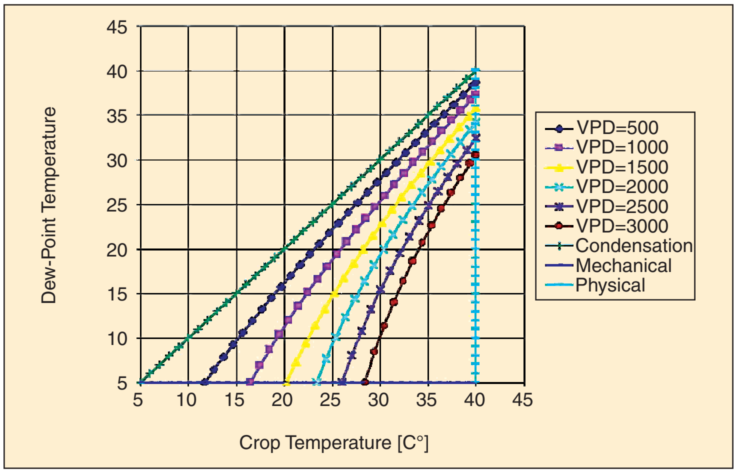

Figure 1. *Operational curves for vapor pressure deficit (VPD) control in a mist propagation system [20].*

the aerial environment (kg·m^{-3}). The parameter Γ is the carbon dioxide compensation point (the concentration at no net photosynthesis, where photorespiration balances photosynthesis). In [2], van Henten presents models for Γ, ε, σ_{CO_2}, and values for the other parameters. Many of the parameters are assumed constant, which is an approximation.

The growth rate coefficient r_{gr} (s^{-1}) can be expressed in a Michaelis-Menten form as follows:

$$r_{gr} = c_{r,gr,\max}\left(\frac{X_n}{X_s + X_n}\right)^{\left(\frac{X_t - 20}{c_{Q10,gr}}\right)}. \tag{7}$$

The greenhouse air temperature is X_t and the $c_{Q10,gr}$ factor is the Q_{10} growth factor for the crop. The saturation growth rate at 20 °C is $c_{r,gr,\max}$ (s^{-1}).

With a crop model in this form, two important state variables can be described and simulated based on three environmental inputs: air temperature, photosynthetic radiation, and aerial carbon dioxide concentration. For a vegetative (only) crop, shoot mass ($X_n + X_s$) becomes the value that is sold.

Greenhouse Climate Models

Although only basic concepts of heat and mass transport are central to a qualitative description of greenhouse climate, the processes must be considered in careful detail to achieve a quantitative description. In particular, the physics of thermal radiation transfer (both solar and "earth temperature") and phase change (primarily evaporation) play central roles in determining the environments of plant canopies. Thermal radiation, convection, phase change, and conduction interact in significant ways. See, for example, [14] for a more complete exposition on the physics of greenhouse climate control.

Assumptions and State Variables

Analysis generally begins with mass and energy balances in a control volume, a volume that frequently is the entire greenhouse. Greenhouses are generally structures having single air spaces, even when they are very large. Moreover, internal mixing fans are often used in an attempt to provide a single, well-mixed air zone within the entire greenhouse. When a thermal screen is used, however, for either light shading or energy retention, the greenhouse must be treated as two interacting air spaces.

Dynamic Models

Many dynamic models for a greenhouse environment exist in the literature. The central state variable is typically air temperature, with relative humidity and carbon dioxide concentration also considered. In [12], Tap describes several models, ending with one that includes heating pipe temperature as well as ventilation, crop transpiration, possible condensation on the structural cover, and solar insolation. The resulting first-order differential equation is a sensible energy balance.

The energy balance is formed on the differential change of thermal energy content of greenhouse air with respect to time. This is balanced by the sum of the following (expressed in simple derivative form): heat exchange by ventilation, heat exchange with the heating pipes, heat exchange with the structural cover, heat exchange with the soil, sensible heat gain from the sun, sensible thermal energy lost due to transpiration, and thermal energy released at the structural cover by water vapor condensation. Note that this form of the energy balance is a lumped-parameter approach. In particular, the soil is subject to thermal changes of long duration and is not truly a lumped parameter, but its effect is usually sufficiently small that this approximation has been successfully used. In certain situations (for example, summer cooling), some terms of the energy balance become unimportant and reduced forms of the model apply.

Transpiration is often modeled after the approach of Penman-Monteith [12]. Condensation at the cover may be simplified by assuming the cover temperature is between the inside and outside air temperature, perhaps near the average (depending on wind, condensation, thermal radiation, and possibly other factors). Ventilation and condensation of water vapor on the structure cover are also treated as quasi-static processes. The results are algebraic equations for each variable.

Greenhouse air humidity is another important state variable that is expressed through a first-order differential equation based on a mass balance. Heating pipe temperature is also expressed through a first-order differential equation sensitive to the circulating water temperature and is assumed to be a lumped-parameter system.

Overview of Control Algorithms in Plant Shoot and Root Environments

Unique Aspects of the Thermal Environment

Disturbances to a greenhouse or other plant thermal environment occur primarily from solar radiation, outside temperature (conduction heat transfer and ventilation heat transfer) and interactions with occupants (plants), the controlled heating and ventilating equipment, and the floor. The generalized dynamic model incorporates these effects, but it is useful to note that, for the most part, the system is subjected to relatively low frequency disturbances. Indeed, most of these disturbances are considered as "loads," and a quasi-steady-state analysis often suffices for design purposes [15], [16]. Perhaps the most common transient disturbance is a step change, either from switching equipment, changing set points, or variable cloud cover.

Similarly, hydroponic systems and plant propagation systems are well damped, and the control algorithms to handle them are often developed from quasi-steady-state considerations [5], [17]-[19]. Fig. 1 illustrates equilibrium process lines between air dew-point temperature and crop canopy temperature for various desired values of crop-to-air vapor pressure deficit [20]. In this example, three cascaded proportional (P) or proportional-integral (PI) controllers were devised to track these process lines, once the interactions between controlled equipment and environment were modeled and validated.

Sensor Issues

Sensors common to plant production include aerial sensors (temperature, relative humidity), radiation or quantum flux sensors (ideally for PAR, but often larger spectrum), and a host of other devices for specialized needs. For example, in hydroponic systems, the circulating nutrient film's electrical conductivity, pH, and dissolved oxygen may be measured. In plant propagation systems where fragile cuttings have not developed root systems, artificial leaf sensors have been used [21] to estimate evaporation from surfaces.

Surprisingly, sensor location can be a significant problem in production facilities. For example, it is not uncommon to find a temperature sensor located in a drafty area of a room or where sunlight may strike it for some time during the day. Obtaining representative environmental measurements is not straightforward for many reasons. Examples include the location of radiation sensors (impact of moving shadows in greenhouses, spectral responses of sensors exposed to nonsolar radiation), aerial environment (temperature or humidity in stratified zones, poorly mixed zones, inability to measure what is wanted, such as within a crop canopy), and sensor technology and maintenance (calibration, drift, noise immunity).

Sensors for water vapor, typically relative humidity sensors, have become increasingly reliable. Humidity control remains a challenge for most operators of production facilities. Newer capacitive-type thin-film technologies offer the capabilities of field swapping, rapid recovery from condensation without offset or bias error, and generally robust performance. However, humidity regulation is difficult, in part due to the inherent sensitivity of relative humidity to air temperature and interactions with thermal radiation.

Sensors for remote acquisition of canopy temperature have become more prevalent. Most utilize some form of infrared technology and assumptions of background emissivity to provide surface temperature of the target area. These sensors make it possible to compute properties such as vapor pressure deficit between crop and air, which previously had to be estimated from other, less direct measurements [22].

Discrete Stage Control

Air temperature control for zones within a large facility, or in small production facilities, is frequently obtained using a series of discrete stages. Stage control systems can be characterized as "discrete proportional controllers" [23]. Their advantages include simplicity of implementation and operation; they are also unconditionally stable controllers [25]. Disadvantages of staged control systems include those of conventional proportional controllers, such as steady-state error, difficulties of tuning for transient response, and the like. Also, generally only ad hoc methods are available to match loads and equipment to controller settings such as hysteresis, dead band, and proportional band between stages. Stage control systems are common, in part because they present a simple interface to users. They can prevent excess energy use caused by both heating and ventilation equipment running simultaneously, and, for many crops, the range in acceptable daytime temperatures is sufficiently broad.

Conventional Dynamic Control

Few commercial systems require conventional dynamic control because of the nature of disturbances typically encountered. Some heating systems incorporate P or PI controllers to modulate valves on hot water or steam systems. Likewise, vents and curtains for fresh ventilation air may incorporate dynamic control. In commercial production, however, these latter systems are often run as a time-based operation, with direct feedback and large lag to match system response to control actions. Specialized research-based facilities may use some form of dynamic control [20], especially if specified conditions are required or desired as part of experimental investigations between environment and plant response. However, a quasi-steady-state controller can be effective for many operations.

Some mechanically ventilated facilities use variable-speed fans and several control systems to incorporate some forms of dynamic control. They are not prevalent, however, because the degree of precision in air temperature control is often not considered necessary. Furthermore, interactions between air temperature and relative humidity, and the discrete nature of air handling equipment used in plant facilities, complicate adoption of dynamic control systems.

Much equipment used in plant production can be classified as binary-switched systems; for example, mist application to plant propagules or two-speed fans. Applications of dynamic control to these systems have recently been made [23], [24] by linearizing each of the dynamic equations for each possible state and controlling the switching rate, similar to pulse-width modulation. A fuzzy PI-like staged controller has been developed to provide superior scaling among different production system sizes and loads [26]. This may be more of a convenience for installation than for operation. An alternative feedback linearization technique is presented, as an example case, at the end of this article.

Model-Based Control

Model-based controllers are prevalent in production and research facilities. Parameters estimated from models are used for load matching and estimation, to tune a control system response, to serve as direct state variables, or to select a different controller for current conditions (adaptive control). Models have been used to estimate the transpiration or evapotranspiration of a crop [4], [27], [28], assimilation of carbohydrates during photosynthesis [4], [13], and nighttime respiration effects [29].

Models may also be used for longer horizon planning, at the crop or seasonal level, rather than for dynamic control [2], [5], [8], [10], [12]. These are discussed in the next section.

The concept of virtual variables (i.e., mathematical models that use measurements to estimate the current state) has been recently elucidated for plant production systems [30], [31]. The general approach has many applications in the literature and is used for both short-term and longer horizon control. Some examples include estimating vapor pressure deficit from measurements of canopy temperature, air temperature, and humidity [20], [22]; estimating evaporation of water from a canopy [18], [21], [27], [28]; and determining time for mist activation based on direct measurement of canopy surface temperature and a modeled "nonwater stressed baseline" temperature [32].

A fundamental stumbling block for the more advanced application of model-based controls is the sparseness, or complete lack, of reliable and inexpensive feedback measures. Thus, adaptive control systems that can handle this uncertainty are under active research. In [29], Chao developed a fuzzy inference system to use a quantitative set of simple measurements on single-stem roses (diameter, length) to evaluate their current state with the desired trajectory generated using a rule base derived from expert opinion. The output of this inference system was used, in conjunction with costs of production and current weather conditions, to determine the proper day and night temperatures for the following one- to three-day period.

Supervisory Systems

As indicated previously, modern plant production control systems incorporate layers of control (current, midrange time horizon, longer time horizon). Although attention to control of the current (instantaneous) state is crucial, and a system must react in a robust manner to faults, this is generally considered insufficient for optimal production.

Midrange-time-horizon controls, such as diurnal or weekly periods, have attracted attention as the understanding of plant physiological needs and reactions to environment has improved. These can be classified as either integrative or trajectory-updating methods. For example, the ability of plants to integrate light exposure for photosynthesis and daily growth has been used to devise control strategies based on daily light integral [8]. Integration of temperature over one or more diurnal cycles is used for temperature set point selection [21], [33]. Continued research is needed to determine plant responses to these longer-term environment manipulations and to interactions with different environment variables. A recently developed floating hydroponic lettuce system maintains both the root and the shoot temperatures independently, at levels determined by careful examination of their interactions [34]. For all but the simplest systems, some form of model-based estimator is generally necessary to update set-point trajectories. The single-stem rose production system described in the previous section is an example [29].

Longer-time-horizon controls, traditionally management's domain in commercial facilities, are emerging as part of complete control systems. One impetus for focusing on longer-time-horizon control systems is to determine optimal trajectories for plant growth; objective functions that constitute this optimal control vary with the application. One notable approach is economically optimal control for commercial production systems, in which it is recognized that the product from the facility may need to be varied to maximize profit as other uncontrolled inputs (costs of energy, weather) vary [4], [29].

Recent Knowledge-Based Control Examples

In [30] and [31], a knowledge-based plant production environment control system is presented that incorporates both current-state and long-time-horizon state control. The current-state controls include discrete staged control, user-specified heuristic algorithms, and proportional-integral-derivative (PID) control. An adaptive optimizer based on a penalty function (user-specified weights) is used to direct population of a dictionary of control regimes as weather and other disturbances change [18]. Midrange-time-horizon trajectory updates are possible using a temperature integration. In [19], it has been demonstrated how the system may be used to alter trajectories for a greenhouse heating policy in an economically optimum fashion. This provided energy savings of up to 20% while remaining within constraints on acceptable climate fluctuations within the greenhouse.

Applications of fuzzy inference systems [35] to plant production environments include a single-stem rose production system [29], [36], [37]. The roses are initially taken as cuttings for stock plants and stuck into media to root. Once rooted, the objective is to produce a uniform crop of single-stem roses rapidly. The control system had multiple layers. The trajectory update system, described earlier, selected subsequent day set-point temperatures. Night set-point temperatures were based on mean daily temperature and integrated PAR; if previous PAR was "large," then the night temperature was adjusted upward to enhance night respiration and enable carbohydrate movement from leaves.

Special Control Problems Related to Growing Plants in Space

Plants are currently grown in space experimentally, but in the near future, we are likely to see them grown in space to supplement crew diets for long-duration missions. Eventually, we may see crews supported entirely by plants grown in space, both directly and as animal feed, just as we do on Earth. There will be disadvantages to this compared to plant production on Earth. Most notably, we have to provide virtually everything for the plants: light, pressure, and so on. However, there are advantages also. If we adequately quarantine the system, there will be no pests or diseases. Weather problems common on Earth are no problem in space.

When growing plants in space, we have to provide virtually everything: lights, pressure, and so on. Advantages are no pests, diseases, or weather problems.

Space is a unique environment for growing plants. In some ways, the environment is easier, but in most ways, the control issues are greater than typically encountered in growing plants on Earth. For experimentation, accurate control of the environment is critical. For production, high growth rates and low cost are critical, as well as high reliability and safety.

Plants and the Space Environment

Space is a hostile environment for life, and we know of nowhere other than Earth where plants can grow outside. There are likely to be extra-solar planets (planets orbiting other stars) where plants can grow, but we have no information yet of such surface environments. Variables in the space environment likely to affect plant growth and not readily controlled include gravity and radiation (ionizing and nonionizing).

Other than the Earth itself, Mars has the most Earth-like environment within the solar system [38]. Daytime temperatures can be suitable for plant growth, rising to 27 °C, but nighttime temperatures fall as low as –143 °C. Surface insolation is lower than on Earth. The maximum is perhaps as low as half that of the Earth, due to Mars' greater distance from the sun. Extensive dust storms can reduce light levels by several orders of magnitude for weeks on end. Day length is slightly longer than the terrestrial day (about 24 h 40 m). However, the main impediments to plant growth on Mars are air pressure (from 0.59 to 1.5 kPa) and the lack of water.

Plants can be grown in space (including the surface of planets and moons) only in artificial environments. The environment used can be tailored to maximize plant growth, rather than copying the terrestrial environment. The partial pressure of carbon dioxide can be elevated above Earth normal; that of oxygen can be reduced. Total pressure can be manipulated. With water and nutrients being readily available and artificial light provided, most conditions for plant growth can be optimized. Data suggest that the optimum concentration of CO_2 is about 1200 ppm. Light levels depend on the crop, with potatoes appearing to have a peak at about 800 $\mu mol \cdot m^{-2} \cdot s^{-1}$ but, with wheat, specific productivity probably continues to rise to at least 2000 $\mu mol \cdot m^{-2} \cdot s^{-1}$ [39], [40].

Space flight is costly. In consequence, high launch mass leads to high mission cost. Power and cooling are provided by systems that are themselves massive, so power and cooling are also costly. Therefore, space systems are generally designed to be light in weight and for low power. Typically, this will result in cramped plant growing conditions and environmental compromises, as well as driving systems to smaller and more reliable sensors (which have payoffs on Earth also).

A spacecraft is a closed environment. Thus, attention must be paid to maintaining all aspects of that environment. The use of flammable items and items that produce offgas is strictly limited. Trace contaminants in the water and air can result from the equipment (e.g., ozone, hydrocarbons), the crew (e.g., methane), or from the plants themselves (notably ethylene). These contaminants must be monitored and, where necessary, controlled.

Control Problems Specific to the Space Environment

The main differences between control in a space environment and control on the ground are the number of parameters that are monitored and controlled and the accuracy expected. In the field, there is typically no control except perhaps watering and feeding. In a greenhouse, temperature and light may also be controlled. In a growth chamber, the degree of environmental control varies from little more than in a greenhouse to almost as much as in space. Environmental parameter response times for space research chambers are likely to be shorter than for typical terrestrial chambers simply because of their small size.

There are unique issues in the space environment that lead to particular control problems. For example, water distribution in a solid matrix is more complex than was anticipated. Rather than the water spreading throughout the substrate by capillarity, it tends to gather in restricted areas, saturating part of the matrix and leaving other parts dry. This may result in a need to monitor the wetness of the substrate in three dimensions, as well as a function of time, and to adjust it appropriately. Similarly, air circulation cannot be taken for granted. In a weightless environment, air circulation depends almost wholly on the use of fans. Without fans, gas exchange would be restricted to diffusion and growth would slow considerably, even where there is some gravity.

Finally, production targets may be quite different. In agriculture, maximum productivity is generally best. In the case of a bioregenerative life support system, there is a limited mass of working material in the system. Overproduction of plants may be as much of a problem as underproduction, complicating distribution of resources around the system and causing resource depletion elsewhere. Thus, it is likely that growth rates must be calculated from the available data and controlled by environment modifications to maintain the desired productivity trajectory. Maintaining a set productivity rate could be difficult. In plant production, variations of 10-20% may be expected. Environmental variability can be reduced in a closed environment, but there are limits. Inherent genetic differences may be a source of variability, even with well-selected propagules. A variation of about 5% can probably be achieved, but this would compare poorly to the variation in performance expected for other spacecraft systems.

Data Transmission and Knowledge Limitations

On Earth, plants are generally grown by professionals. When there is a problem with a crop of plants, there is a large support infrastructure, from the expertise of researchers to local extension offices. In space, on the other hand, the work may be performed by a flight crew with little knowledge of plant growth and with minimal training on the equipment (due to other training requirements). Communications may be inadequate or nonexistent, and terrestrial expertise may be unavailable. As we travel to other planets, transmission lags will become significant. On Mars, two-way transmission lags can range from 15 minutes to over an hour. Communication may be nonexistent when Earth and Mars are on opposite sides of the sun or due to communication equipment failures. Limits to growth will generally be a result of system problems. Some of these will be control problems, and most can be ameliorated by control actions.

Adequate knowledge and fault detection may be built into control systems to deal with anomalies, and extensive additional information may be needed for virtually any contingency. The control system will require the capability to act as an expert system. Expert systems are only able to respond to problems they were designed to resolve. Other artificial intelligence systems may be able to extrapolate beyond this. Robustness is important, for space is a challenging environment. The system must be designed to cope with anomalies, including power spikes and dropouts, and must fail gracefully.

Radiation Effects on the Control System

The control system itself is not immune to environmental influences. Modern control systems are heavily dependent on computer technology. Commercial computer chips are generally made from etched silicon, and the feature size is rapidly shrinking. Ionizing radiation can cause a number of problems with computer chips. In particular, it can permanently damage the chip (a "hard" upset) or change the state of a gate (a "soft" upset). These types of damage must be considered when designing a control system for a space application. Soft upsets can be reset; hard upsets must be worked around or the hardware replaced. In summary, a space control system for growing plants will be expected to deal with more data and different challenges. These problems will require control system redundancy, good designs that are robust when faced with anticipated problems, and testing in relevant environments.

The Greenhouse Dynamic Control System

An example of a coupled, nonlinear controller for air temperature and humidity in a greenhouse is developed in this section. The dynamic model is obtained from energy and mass balances on the enclosed greenhouse air and is shown to be highly nonlinear. Several methods of feedback and feedforward control appropriate for this example system are presented.

Complete Nonlinear Model

A simple greenhouse heating-cooling ventilating model can be obtained by considering the differential equations that govern sensible heat and water vapor balances on the interior volume. These differential equations are as follows:

$$\frac{dT_{\text{in}}(t)}{dt} = \frac{1}{\rho C_p V}\left[q_{\text{heater}}(t) + S_i(t) - \lambda q_{\text{fog}}(t)\right] - \frac{\dot{V}(t)}{V}\left[T_{\text{in}}(t) - T_{\text{out}}(t)\right] - \frac{\text{UA}}{\rho C_p V}\left[T_{\text{in}}(t) - T_{\text{out}}(t)\right] \tag{8a}$$

$$\frac{dw_{\text{in}}(t)}{dt} = \frac{1}{\rho V} q_{\text{fog}}(t) + \frac{1}{\rho V} E\left(S_i(t), w_{\text{in}}(t)\right) - \frac{\dot{V}(t)}{\rho V}\left[w_{\text{in}}(t) - w_{\text{out}}(t)\right] \tag{8b}$$

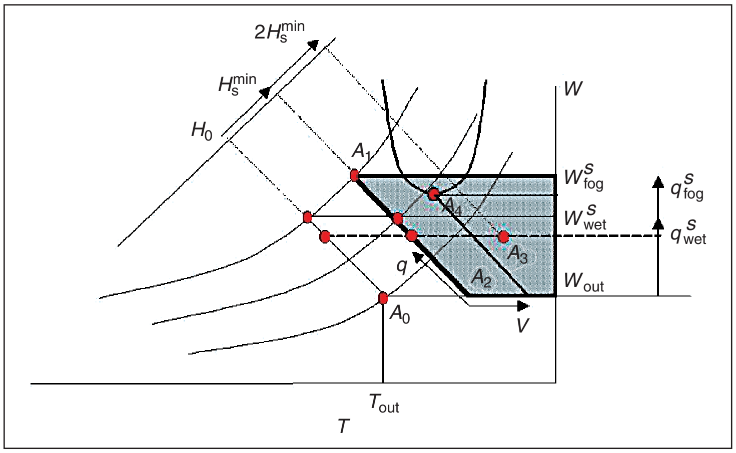

Figure 2. *Actuation limits defined by psychrometric properties. Point A_1 is the operational condition at maximum capacity of ventilation and misting. Point A_3 is achieved if 50% capacity is used. Note that air properties at A_3 are drier and hotter than at A_1.*

where T_{in} is indoor air temperature (°C), T_{out} is outdoor temperature (°C), V is greenhouse volume (m^3), UA is the heat transfer coefficient (W·K^{-1}), ρ is air density (1.2 kg·m^{-3}), C_p is specific heat of air (1006 J·(kg·K)$^{-1}$), q_{heater} is the heat provided by the greenhouse heater (W), S_i is the intercepted solar radiant energy (W), q_{fog} is the water capacity of the fog system (g H_2O·s^{-1}), λ is the latent heat of vaporization (2257 J·g^{-1}), $\dot{V}$ is the ventilation rate (m^3·s^{-1}), w_{in} and w_{out} are the interior and exterior humidity ratios (water vapor mass ratio, g H_2O·kg^{-1} of dry air), respectively, and $E(S_i, w_{in})$ is the evapotranspiration rate of the plants (g H_2O·s^{-1}). It should be noted that the air volume (V) to be used in the balances is the effective mixing volume. Short circuiting and stagnant zones exist in ventilated spaces, and the effective mixing volume is typically significantly less than the calculated total volume. The effective mixing volume of a ventilated space may easily be as small as 60 to 70% of the geometric volume. This, of course, means indoor air temperature is unlikely to be uniform throughout the air space.

Greenhouse Thermal Model

Temperature and relative humidity are commonly measured air properties, highly coupled through nonlinear thermodynamic laws; for example

$$w = f(T,\mathrm{RH},P) = \frac{0.62198 \cdot P_{ws}(T)\cdot \mathrm{RH}}{P - P_{ws}(T)\cdot \mathrm{RH}} \tag{9}$$

where P is atmospheric pressure (kPa) and P_{ws} is saturation pressure of water vapor (kPa). Conversion of relative humidity RH to humidity ratio, using (9), provides a first step toward a state decoupled and linearized system.

We define a specific enthalpy change (H_s) as the energy per unit volume (J·m^{-3}) carried by the ventilating air. A thermal balance, neglecting enthalpy of incoming air and conductive heat losses from the greenhouse, yields

$$H_s\dot{V} = S_i \Rightarrow H_s = \frac{S_i}{\dot{V}}. \tag{10}$$

The actuating capacity q_{fog}^{max} is selected to ensure that ventilation air changed ($\dot{V}^{max}$) can be saturated under any load conditions. Moreover, let w_{wet}^s, w_{fog}^s be the water-carrying capacity of the saturated air for wet-pad and fog system operation, respectively, and q_{wet}^s, q_{fog}^s be the effective water-carrying capacity, from w_{out} to saturation, for wet-pad and fog systems, respectively (Fig. 2). The actuating limit is $q_{fog}^{max} = q_{fog}^s\dot{V}$.

Maximum cooling is achieved when maximum evaporated water is used for a given ventilation rate; thus, a control-feasible region is defined based on maximum ventilation capacity. In this condition the minimum specific enthalpy is

$$H_s^{min} = \frac{1}{\dot{V}^{max}} S_i. \tag{11}$$

Equation (10) defines the feasible region to the right of line A_1-A_2, drawn as the locus of $H_o + H_s^{min}$, as shown in Fig. 2. For example, at half capacity with $q_{fog} = q_{fog}^{max}/2$ and $\dot{V} = \dot{V}^{max}/2$, $H_s = 2H_s^{min}$, and starting from outside conditions at point A_0, the operating point will be <A_3> instead of <A_1> at full capacity.

The decision for a desired point of operation inside the feasible region is based on a cost function of the form:

$$J = c_1(T_{in,sp} - T_{in,d})^2 + c_2(\mathrm{RH}_{in,sp} - \mathrm{RH}_{in,d})^2 + c_3\dot{V} + c_4 q_{fog}.$$

Depending on the outside air conditions and the load S_i, the achievable conditions, for any cost, may not be the desirable ones ($T_{in,d}$, $\mathrm{RH}_{in,d}$). A rule base can be used to assign values for cost parameters c_1 and c_2 so as to equalize the risk on the crop from the deviations ($T_{in,sp} - T_{in,d}$) and ($\mathrm{RH}_{in,sp} - \mathrm{RH}_{in,d}$). In an attempt to use complete functionals for cost calculations, without resorting to fuzzy rules for cost assignments, we used the following extended cost function:

$$J = c_1(T_{in,sp} - T_{in,d})^2 + \frac{c_1^*}{T_{in,sp} - T_{in,max}} + c_2(\mathrm{RH}_{in,sp} - \mathrm{RH}_{in,d})^2 + \frac{c_2^*}{1 - \mathrm{RH}_{in,sp}} + c_3\dot{V} + c_4 q_{fog}. \tag{12}$$

The added penalty function terms ensure that the calculated set points for temperature and humidity are kept away from an absolute maximum temperature (chosen by intuition and constraints for crop safety) and from the saturation line (risk of disease).

A gradient descent method for minimizing (12) subject to constraints given by (9)-(11) and the system load depicted in Fig. 3 as Env(S_i, T_{out}, RH_{out}), can be devised. A precompensator and variable translator (PVT) calculates the realizable desirable target conditions $T_{\text{in},sp}$ and $w_{\text{in},sp}$, the control values of q_{fog} and $\dot{V}$ (which can be used as feedforward values), and other variables useful for the calculations at the controller. The PVT has all the required logic to compute realizable set points and avoid pitfalls (i.e., singular values in $\Delta(t)$ calculations of (15a) and (15b) below) by post-processing the solution of (12).

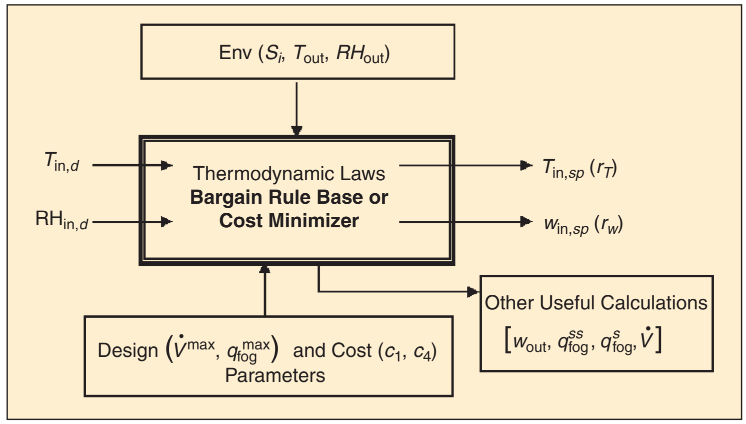

Figure 3. *Precompensator and variable translator for calculating feasible control targets.*

Control Model

For summer operation, q_{heater} in (8a) is set to zero. It is also worth noticing that, to a first approximation, the evapotranspiration rate $E(S_i(t), w_{\text{in}}(t))$ is in most part related to the intercepted solar radiant energy through the following simplified relation:

$$E(S_i(t), w_{\text{in}}(t)) = \alpha \frac{S_i(t)}{\lambda} - \beta_T w_{\text{in}}(t) \tag{13}$$

where α is an overall coefficient to account for shading and leaf area index and β_T is an overall coefficient to account for thermodynamic constants and other factors affecting evapotranspiration (i.e., stomata, air motion, etc.). Moreover, defining the inside temperature and the inside absolute humidity as the dynamic state variables, $x_1(t)$ and $x_2(t)$, respectively, the ventilation rate and the water capacity of the fog system as the control (actuator) variables, $u_1(t)$ and $u_2(t)$, respectively, and the intercepted solar radiant energy, the outside temperature, and the outside absolute humidity as the disturbances, $v_i(t), i = 1,2,3$, of the model, (8a) and (8b) can be put in the following state-space form:

$$\begin{aligned}\dot{x}_1(t) = &-\frac{\text{UA}}{\rho C_p V} x_1(t) - \frac{1}{V} x_1(t) u_1(t) - \frac{\lambda}{\rho C_p V} u_2(t)\\ &+ \frac{1}{\rho C_p V} v_1(t) + \frac{\text{UA}}{\rho C_p V} v_2(t) + \frac{1}{V} u_1(t) v_2(t)\end{aligned} \tag{14a}$$

$$\begin{aligned}\dot{x}_2(t) = &-\frac{\beta_T}{\rho V} x_2(t) + \frac{1}{\rho V} u_2(t) + \frac{\alpha}{\lambda \rho V} v_1(t)\\ &- \frac{1}{\rho V} x_2(t) u_1(t) + \frac{1}{\rho V} u_1(t) v_3(t).\end{aligned} \tag{14b}$$

Equation (14) is a coupled nonlinear equation, which cannot be put into the rather familiar form of an affine analytic nonlinear system, due to the cross-product terms between control and disturbance variables. Other data-based approaches have also been successfully applied to reduce the complexity of the model and design a control system with good disturbance-response characteristics.

Feedback/Feedforward Linearization

It is well known that affine nonlinear systems may be globally linearized and decoupled by nonlinear feedback. This is just the scheme of inverse dynamic control. The extension of this scheme to more complex cases, such as the one represented by (14), is sometimes feasible, since the disturbance variables of the greenhouse heating-cooling ventilating model can be readily measured. Furthermore, the complexity of such systems may be eased by the fact that (as discussed earlier) the system state changes slowly and some state-dependent parameters (i.e., β_T) can be considered constant (i.e., quasi-static system operation). Therefore, in the present case, a combined scheme of feedback with simultaneous feedforward linearization is plausible.

To this end, consider the following nonlinear feedback with simultaneous feedforward control law:

$$u_1(t) = \frac{\rho C_p V \tilde{K}_T \tilde{u}_T(t) + \lambda V \tilde{K}_w \tilde{u}_w(t) - (\alpha + 1) v_1(t) - \text{UA} v_2(t)}{\rho C_p [v_2(t) - x_1(t)] + \lambda [v_3(t) - x_2(t)]} \tag{15a}$$

and see (15b) at the bottom of the page, where $\tilde{u}_T(t)$ and $\tilde{u}_w(t)$ are new external inputs and $\tilde{K}_T, \tilde{K}_w$ are process gains. The above control law is feasible if the denominator

$$\Delta(t) \equiv \rho C_p [v_2(t) - x_1(t)] + \lambda [v_3(t) - x_2(t)]$$

is different from zero. Note that in the case where $\Delta(t) = 0$, the input $u_1(t)$ affects the system states $x_1(t)$ and $x_2(t)$ the same way as $u_2(t)$; in this case, decoupling, as well as feedback-feedforward linearization, is impossible.

$$u_2(t) = \frac{\left(\rho C_p V \tilde{K}_T \tilde{u}_T(t) - v_1(t) - \text{UA} v_2(t)\right)(x_2(t) - v_3(t)) + \rho C_p V\,(v_2(t) - x_1(t)) \tilde{K}_w \tilde{u}_w(t) + \frac{\rho \alpha C_p}{\lambda}(x_1(t) - v_2(t))\, v_1(t)}{\rho C_p\,(v_2(t) - x_1(t)) + \lambda\,(v_3(t) - x_2(t))} \tag{15b}$$

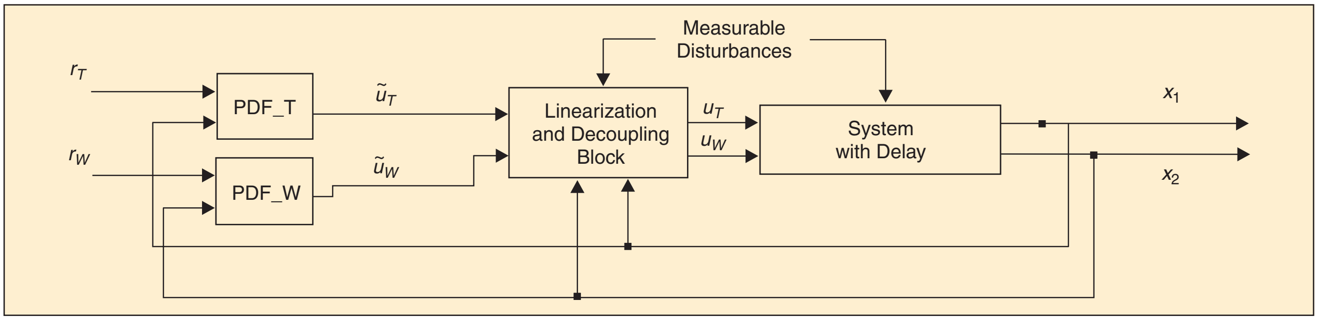

Figure 4. *Overall control strategy in case of small time delays and/or a slow desired response.*

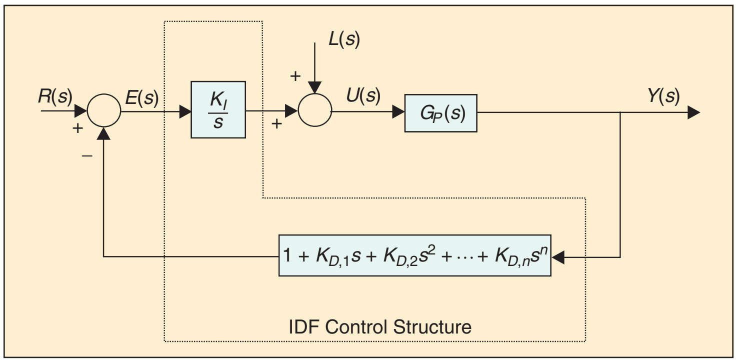

Figure 5. *The general IDF control structure.*

By applying this control law (15) in the nonlinear model (14a), (14b), the resulting closed-loop system is linearized and decoupled, having the form

$$\dot{x}_1(t) = -\frac{\mathrm{UA}}{\rho C_p V} x_1(t) + \tilde{K}_T \tilde{u}_T(t) \tag{16a}$$

$$\dot{x}_2(t) = -\frac{\beta_T}{V} x_2(t) + \tilde{K}_w \tilde{u}_w(t). \tag{16b}$$

The greenhouse interior temperature and relative humidity are measured by a thermometer and a hygrometer, respectively, usually located a certain distance from the greenhouse ventilators and the fog or wet-pad system. Hygrometers can present significant lag time. Hence, the changes in the temperature and absolute humidity are determined after a certain dead time d_T and d_w, respectively ($d_T < d_w$). With this observation, it is easy to check that the response to input changes can be described by the following transfer function models:

$$X_1(s) = \frac{K_T e^{-d_T s}}{\tau_T s + 1} \tilde{U}_T(s) \equiv G_T(s) \tilde{U}_T(s) \tag{17a}$$

$$X_2(s) = \frac{K_w e^{-d_w s}}{\tau_w s + 1} \tilde{U}_w(s) \equiv G_w(s) \tilde{U}_w(s) \tag{17b}$$

where $X_1(s)$, $X_2(s)$, $\tilde{U}_T(s)$, and $\tilde{U}_w(s)$ are the Laplace transforms of $x_1(t)$, $x_2(t)$, $\tilde{u}_T(t)$, and $\tilde{u}_w(t)$, respectively, and where

$$\tau_T = \frac{\rho C_p V}{\mathrm{UA}}, \quad K_T = \frac{\rho C_p V}{\mathrm{UA}} \tilde{K}_T, \quad \tau_w = \frac{V}{\beta_T}, \quad K_w = \frac{V}{\beta_T} \tilde{K}_w.$$

At summer evaporative cooling conditions and for certain crops, the term $\beta_T w_{\text{in}}(t)$ of (13) is relatively weak. To meet the real difficulty of the water addition process, if we choose to omit this term, the second state equation (14b) becomes a perfect integrator. Indeed, in this case, relations (16b) and (17b) take the following respective forms:

$$\dot{x}_2(t) = \tilde{K}_w \tilde{u}_w(t) \tag{18a}$$

$$X_2(s) = \frac{\tilde{K}_w e^{-d_w s}}{s} \tilde{U}_w(s) \equiv \tilde{G}_w(s) \tilde{U}_w(s). \tag{18b}$$

On the basis of (17a) and (18b), temperature changes are modeled by a self-regulating first-order plus dead-time (FOPDT) model while humidity ratio changes are modeled by an unstable integrator plus dead-time model. We are now able to control temperature and absolute humidity separately using several types of simple controllers (PID controllers, predictive controllers, etc.). In this example, to perform the tuning, we prefer to use pseudo-derivative feedback (PDF) controllers [41], [42]. The overall control strategy when such controllers are used is depicted in Fig. 4.

Pseudo-Derivative Feedback Controllers

The general PDF control structure is a modification of the integral control with derivative-feedback (IDF) algorithm. The IDF algorithm has an integrator in the forward path where the controller is usually located (e.g., a PI controller) and derivative feedback on the controlled variable. A general schematic diagram of the IDF algorithm is given in Fig. 5. Mathematically, this idealized controller works well, but in practical applications, derivatives of the control variable show significant noise, especially for the second- and higher-order derivatives.

The general PDF control structure is different. Instead of feeding back the derivative of the controlled variable in order to calculate the actuating signal, then integrating this component in the forward loop, all of the controlled variable derivative feedback is bypassed to the integrator output. This approach reduces the number of derivatives by one. A schematic diagram of the general PDF control structure is depicted in Fig. 6. Although the control coefficients for the IDF algorithm and the general PDF control structures are different, simulations show that they have similar response. Other generic controllers, such as the proportional-integral-plus (PIP), can provide high-order derivative action without the need for explicit differentiation and can be interpreted in optimal terms. Moreover, PIP control can be implemented in full multivariable, decoupling form and can mimic most other recent controllers.

Actually, the PDF controller is a variation of the conventional PID controller, differing in the following main points:

- The standard PID controller configuration usually consists of a proportional gain that multiplies a dynamic part containing the integrating and derivative actions, with all the controller elements located in the forward path. In contrast, the elements of the PDF controller are appropriately located in both the forward and the feedback paths. This configuration contributes to a better understanding of the controller action, since the elements located in the feedback path (which are related to the proportional and derivative controller actions) are mainly dedicated to obtaining the desired closed-loop performance (stability, responsiveness, disturbance attenuation, etc.), whereas the forward path elements (relative to integral action) are used for steady-state error elimination.
- The conventional PID controller acts on the process error with the result that each element contributes to closed-loop poles as well as closed-loop zeros. In contrast, as will become clear later on, the PDF controller elements do not contribute to closed-loop zeros, and hence they do not enhance overshoot in the closed-loop response.
- PDF controllers can realize critical damping with faster settling time than a PID controller with overshoot.
- In PDF controllers there is no need for integrator windup. No matter what overload conditions occur, the system never needs to "recover control."
- In the case of PDF controllers, not only is there no steady-state error, but the control system can be made immune to steady-state departure from the ideal response to a ramp by adding a higher-order derivative.

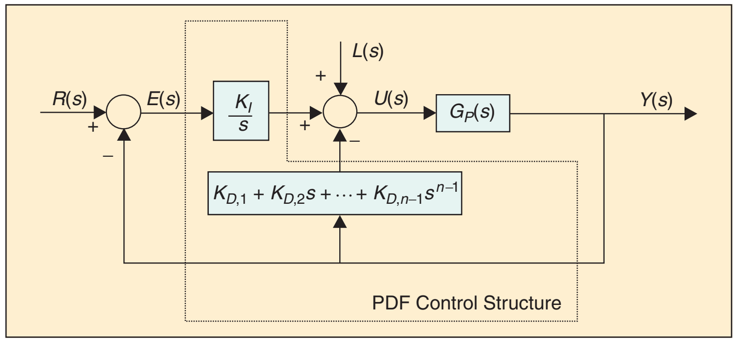

Figure 6. *The general PDF control structure.*

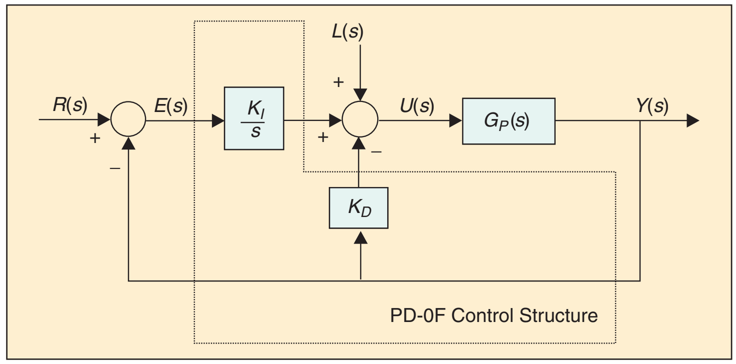

Figure 7. *The PD-0F control structure applied to a process model.*

- The response to load variations when a PDF controller is used is better than that obtained by PID controllers.

In the present example, we focus our attention on the simplest possible case of the general PDF control structure, depicted in Fig. 7. We call this feedback scheme the PD-0F control structure. We shall next analyze the behavior of this specific feedback scheme, especially in the case where the system under control is an FOPDT or an IPDT process with transfer functions as in (17a) and (18b).

To this end, observe that for an FOPDT model of the form (17a) or for an IPDT model of the form (18b), the transfer function of the closed-loop system $G_{CL}(s)$ takes the form

$$G_{CL}(s) = \frac{K_I G_p(s)}{s + (K_D s + K_I) G_p(s)} \tag{19}$$

where $G_p(s) = G_T(s)$ or $G_w(s)$. Substituting separately (17a) and (18b) in (19), we obtain

$$G_{CL,T}(s) = \frac{\exp(-d_T s)}{s\left(\frac{\tau_T}{K_T K_{I,T}} s + \frac{1}{K_T K_{I,T}}\right) + \left(\frac{K_{D,T}}{K_{I,T}} s + 1\right)\exp(-d_T s)} \tag{20a}$$

$$G_{CL,w}(s) = \frac{\exp(-d_w s)}{\frac{1}{\tilde{K}_w K_{I,w}} s^2 + \left(\frac{K_{D,w}}{K_{I,w}} s + 1\right)\exp(-d_w s)}. \tag{20b}$$

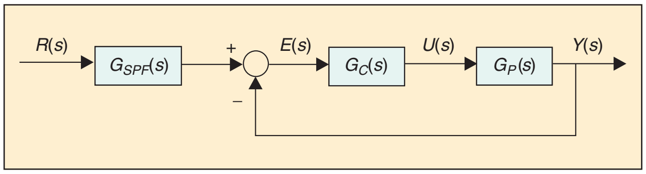

Figure 8. *PI controller with set-point filter control structure equivalent to PD-0F control.*

Clearly, the control structure of Fig. 7 is equivalent to the control structure of Fig. 5, in the case where $K_{D,2} = K_{D,3} = \ldots = K_{D,n} = 0$ and $K_{D,1} = K_D / K_I$ and $G_P(s)$ is given by (17a) or (18b). Moreover, the proposed control structure is equivalent to a conventional PI control with the set-point filter feedback control structure of Fig. 8, where

$$G_C(s) = K_D\left(1 + \frac{1}{\theta s}\right), \quad G_{SPF}(s) = \frac{1}{\theta s + 1}, \quad \theta = K_D/K_I. \tag{21}$$

Therefore, the PDF structure internalizes a prefilter that one would apply to cancel any zeros introduced in the PI (or PID) equivalent system. Thus, the PDF structure can be used in lieu of a PI (or PID) compensator where one may also be using a prefilter to eliminate overshoot.

Tuning of the PD-0F Controller

In tuning the PD-0F controller for FOPDT and IPDT models, the designer tries to satisfy several objectives considering the performance as well as the robustness of the closed-loop system. Many tuning methods for simple controllers are now available for achieving single objectives such as decay ratio, phase and gain margins, resonant peak and frequency, overshoot, and certain error integral criteria.

A simple method for tuning the PD-0F controller is as follows: Let the desired responses be described by the following models:

$$H_T(s) = \frac{\exp(-d_T s)}{\lambda_T s + 1}, \quad H_w(s) = \frac{\exp(-d_w s)}{\lambda_w s + 1} \tag{22}$$

where λ_T and λ_w, respectively, are the desired time constants. Then, equating (20a) with the first equation of (22) and (20b) with the second equation, using the following approximations for the exponential term in the denominator of (20a) and (20b):

$$\exp(-d_T s) \cong 1 - d_T s, \exp(-d_w s) \cong 1 - d_w s \tag{23}$$

and equating like powers of s in the resulting relations, we obtain

$$K_{D,T} = \frac{\tau_T}{K_T d_T}, \qquad K_{I,T} = \frac{d_T + \tau_T}{K_T d_T(\lambda_T + d_T)}$$
$$K_{D,w} = \frac{1}{d_w \tilde{K}_w}, \qquad K_{I,w} = \frac{1}{d_w \tilde{K}_w(\lambda_w + d_w)}.$$

Unfortunately, although this tuning is very simple, it is also defective, because to obtain a closed-loop system that satisfactorily matches the desired model, one must select λ_T (λ_w) to be much larger than the dead time d_T (d_w) [$\lambda_T(\lambda_w) > 10 d_T(d_w)$ or more], thus producing a very sluggish response. To allow faster responses, a method based on the matching of closed-loop system characteristics to those of a prespecified second-order plus dead-time model must be utilized. This method is as follows:

On the basis of (23), relations (20a) and (20b) become

$$G_{CL,T}(s) = \frac{\exp(-d_T s)}{\tau_{e,T}^2 s^2 + 2\zeta_T \tau_{e,T} s + 1} \tag{24a}$$

$$G_{CL,w}(s) = \frac{\exp(-d_w s)}{\tau_{e,w}^2 s^2 + 2\zeta_w \tau_{e,w} s + 1} \tag{24b}$$

$$\tau_{e,T} = \sqrt{\frac{\tau_T}{K_T K_{I,T}} - \frac{d_T K_{D,T}}{K_{I,T}}}, \quad \zeta_T = \frac{\dfrac{1}{K_T K_{I,T}} + \dfrac{K_{D,T}}{K_{I,T}} - d_T}{2\sqrt{\dfrac{\tau_T}{K_T K_{I,T}} - \dfrac{d_T K_{D,T}}{K_{I,T}}}} \tag{25}$$

$$\tau_{e,W} = \sqrt{\frac{1}{\tilde{K}_w K_{I,w}} - \frac{d_w K_{D,w}}{K_{I,w}}}, \quad \zeta_W = \frac{\dfrac{K_{D,w}}{K_{I,w}} - d_w}{2\sqrt{\dfrac{1}{\tilde{K}_w K_{I,w}} - \dfrac{d_w K_{D,w}}{K_{I,w}}}}. \tag{26}$$

Now selecting $\tau_{e,T} = \tau_{e,T,\mathrm{des}}$ and $\zeta_T = \zeta_{T,\mathrm{des}}$ and solving (25) with respect to $K_{D,T}$ and $K_{I,T}$, we obtain

$$K_{D,T} = \frac{\tau_T}{d_T K_T} - \frac{\tau_{e,T,\mathrm{des}}^2 (d_T + \tau_T)}{d_T K_T\left(2 d_T \zeta_{T,\mathrm{des}} \tau_{e,T,\mathrm{des}} + \tau_{e,T,\mathrm{des}}^2 + d_T^2\right)}$$
$$K_{I,T} = \frac{d_T + \tau_T}{K_T\left(2 d_T \zeta_{T,\mathrm{des}} \tau_{e,T,\mathrm{des}} + \tau_{e,T,\mathrm{des}}^2 + d_T^2\right)}.$$

Similarly, selecting $\tau_{e,w} = \tau_{e,w,des}$, $\zeta_w = \zeta_{w,\mathrm{des}}$ and solving (26) with respect to $K_{D,w}$ and $K_{I,w}$, we obtain

$$K_{D,w} = \frac{1}{d_w \tilde{K}_w} - \frac{\tau_{e,w,\mathrm{des}}^2}{d_w \tilde{K}_w\left(2 d_w \zeta_{w,\mathrm{des}} \tau_{e,w,\mathrm{des}} + \tau_{e,w,\mathrm{des}}^2 + d_w^2\right)}$$
$$K_{I,w} = \frac{1}{\tilde{K}_w\left(2 d_w \zeta_{w,\mathrm{des}} \tau_{e,w,\mathrm{des}} + \tau_{e,w,\mathrm{des}}^2 + d_w^2\right)}.$$

Remark: It is worth noting that, in selecting $\tau_{e,T,\mathrm{des}}$ and $\zeta_{T,\mathrm{des}}$ (respectively, $\tau_{e,w,\mathrm{des}}$ and $\zeta_{w,\mathrm{des}}$), one must keep in mind that the nonlinear feedback-feedforward control law (15a), (15b), which renders the overall system linear and decoupled, relies on current state and disturbance measurements.

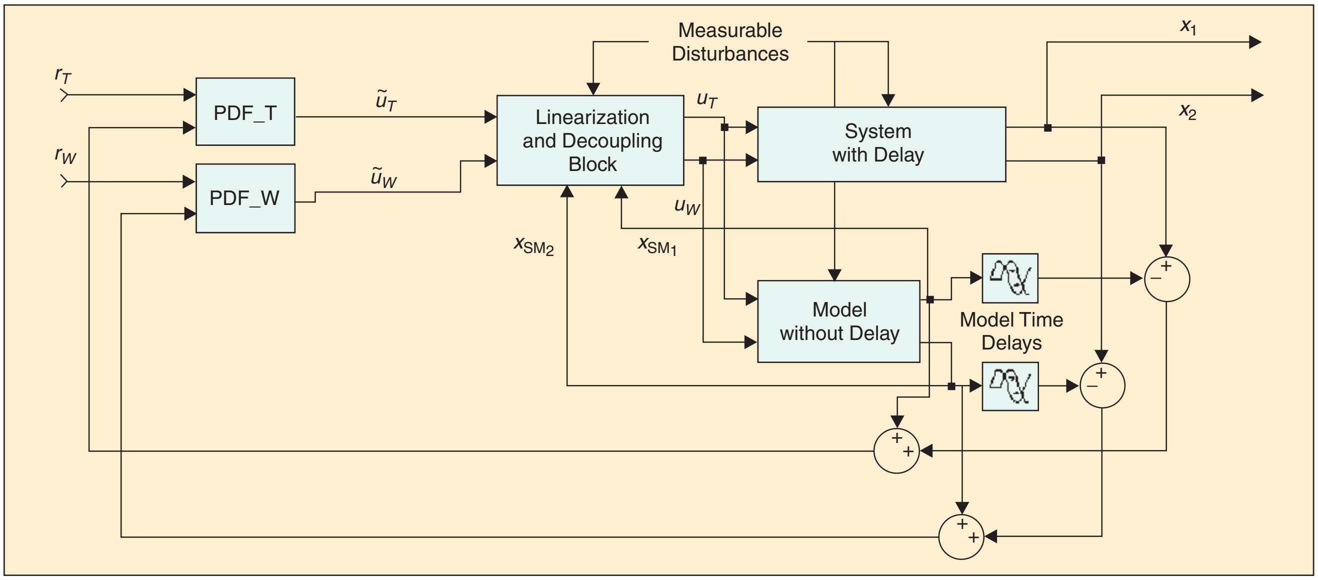

Figure 9. *Overall control strategy in the case of large time delays and/or a fast desired response.*

Therefore, time delays may affect the feedback-feedforward linearization procedure and could degrade its performance. To avoid this problem, one must select $\tau_{e,T,\mathrm{des}}$ and/or $\zeta_{T,\mathrm{des}}$ (respectively, $\tau_{e,w,\mathrm{des}}$ and/or $\zeta_{w,\mathrm{des}}$), which are related to the speed of the closed-loop system response, to be large enough to result in a relatively slow closed-loop system. For example, either $\tau_{e,T,\mathrm{des}} > 4d_T$ ($\tau_{e,w,\mathrm{des}} > 4d_w$) and/or $\zeta_{T,\mathrm{des}} > 1$ ($\zeta_{w,\mathrm{des}} > 1$) appear to be quite satisfactory compromises between the speed of the closed-loop system response and the performance of the feedback-feedforward linearizing control law. However, when faster responses are desired, then to avoid problems interwoven with the performance of the feedback-feedforward linearization procedure, one could use a Smith predictor, which, in addition, can compensate for large time delays d_T or d_w. This alternative strategy is depicted in Fig. 9 and has been practiced with systems of longer time delays, as in [31].

Another method for tuning PD-0F controllers for FOPDT and IPDT process models is based on the equivalence of the PD-0F controller with the conventional PI with set-point filter feedback control structure, mentioned above, and the satisfaction of desired phase and gain margin specifications. For FOPDT models, acceptable PI controller tunings based on this method have been proposed in [43], whereas for IPDT process models, analogous results have been reported in [44].

In the present example of a generalized controller for greenhouse environments, to ensure proper operation of the feedback-feedforward linearizing and decoupling controller, stability margin specifications must be assigned carefully to avoid a very fast closed-loop response. However, if a fast response is desired, the use of a Smith predictor is again indispensable.

If a single performance objective is all that is required, then the equivalence between the PD-0F control structure and the PI with set-point filter control structure permits us to readily extend a wide variety of tuning methods developed for PI controllers (e.g., see [43]-[48] and the references cited therein). However, if the satisfaction of more than one control design objective is desired (e.g., the satisfaction of certain phase and gain margins, the maximization of resonant frequency, or the minimization of a weighted integral of squared error), then the multi-objective design method reported in [48] (see also the references therein) may be used. This tuning technique is based on the solution of a multi-objective optimization problem via a simplified goal attainment formulation.

Generalizing somewhat from this example, in the case where the term $\beta_T w_{\mathrm{in}}(t)$ of (13) is not negligible, an FOPDT model of the form (17b) is obtained, which can be controlled by a PD-0F controller, tuned according to the methods presented above, for the case of a temperature model of the form (17a).

As will be shown, the proposed control algorithm, based on feedback/feedforward linearization and PD-0F controllers, is quite robust to system parametric uncertainty as well as load disturbances. In particular, a 10% uncertainty can be easily tolerated by the proposed controller. However, in the case of large parameter variations (e.g., plant growth that in turn affects greenhouse thermal capacity and evapotranspiration), one must apply more sophisticated control algorithms (e.g., robust control or adaptive control algorithms). Research on these topics is currently in progress [49], [50].

Simulation Results

The effectiveness of the proposed PD-0F control scheme is demonstrated by a case study. For this example, consider a greenhouse of surface area 1000 m^2 and a height of 4 m. The greenhouse has a shading screen that reduces the incident solar radiant energy by 60%. The maximum water capacity of the fog system is 26 g $H_2O \cdot min^{-1} \cdot m^{-3}$. Maximum ventilation rate corresponds to 20 air changes per hour (22.2 $m^3 \cdot s^{-1}$). Parame-

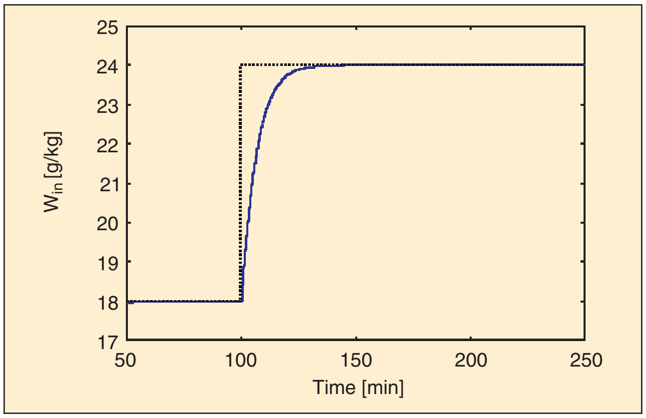

Figure 10. *Response of absolute humidity w_{in} for step changes in both humidity and temperature.*

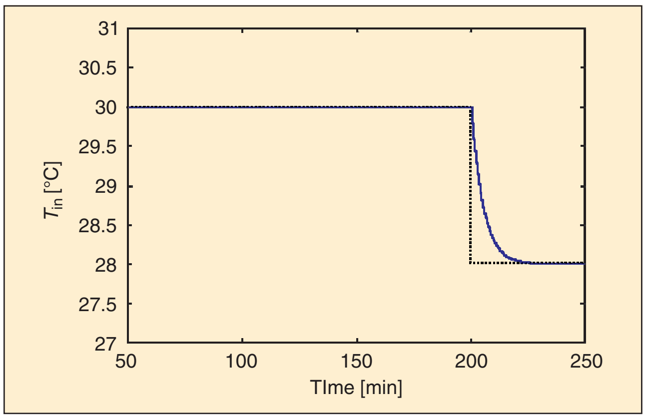

Figure 11. *Response of temperature T_{in} for step changes in both humidity and temperature.*

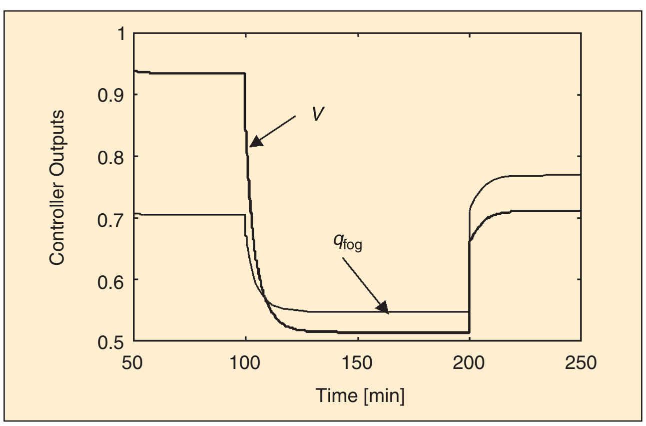

Figure 12. *Controller outputs for step changes in both humidity and temperature.*

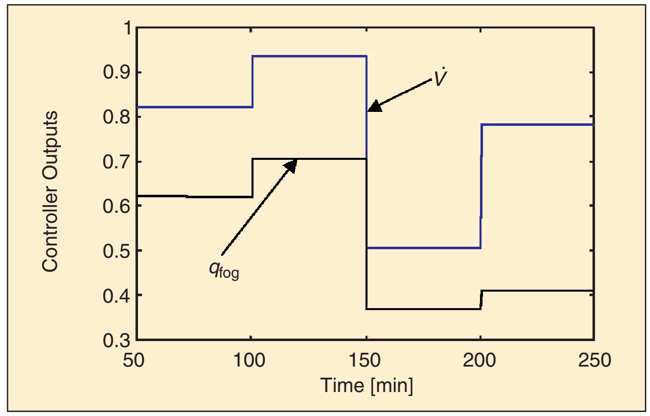

Figure 13. *Controller outputs for step changes in external disturbances (weather conditions).*

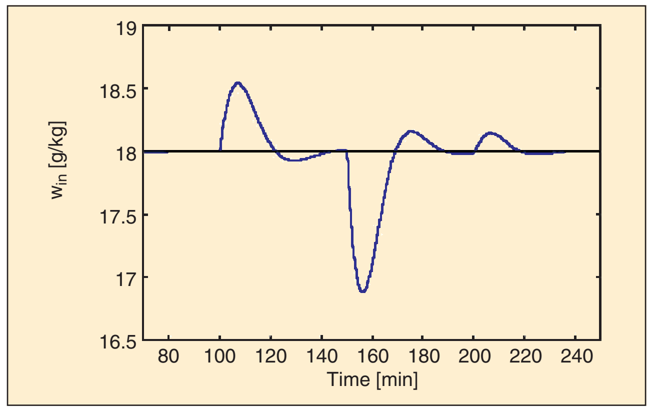

Figure 14. *Regulation of humidity ratio w_{in} for step changes in external disturbances in case of uncertainty.*

ter α/λ takes the value 3.32×10^{-3} g$\cdot$(min$\cdot$W)$^{-1}$, and β_T is assumed to be negligible. The heat transfer coefficient is UA = 25 kW$\cdot$K^{-1}. Finally, we assume that unknown system and sensor dynamics contribute an overall dead time of 0.5 min in both temperature and humidity measurements (i.e., $d_T = d_w = 0.5$ min).

A first simulation experiment has been conducted to demonstrate the ability of the proposed control scheme to provide noninteracting control and smooth closed-loop response to set-point step changes. To this end, we select $\tilde{K}_T = \tilde{K}_w = 1$. Then, after applying the feedback plus feedforward linearizing and decoupling control law, we obtain the decoupled systems of the form (17a) and (18b), with $K_T = 13.3333$, $\tau_T = 13.3333$ min. Our purpose is to design two individual PD-0F control loops for these two subsystems to achieve the desired performance, as represented by relations (20a) and (20b). We select here $\zeta_{T,\text{des}} = \zeta_{w,\text{des}} = 1$ and $\tau_{e,T,\text{des}} = \tau_{e,w,\text{des}} = 2.5$ min. With the above specifications, we obtain $K_{D,T} = 0.5590$ and $K_{I,T} = 0.1153$, while $K_{D,w} = 0.6111$ and $K_{I,w} = 0.1111$. These two controllers were implemented in simulation, and the responses for set-point step changes in humidity ratio and temperature are given in Figs. 10 and 11, respectively. The humidity ratio set point was raised from 18 g/kg to 24 g/kg (which corresponds to a relative humidity change from 60% to 80%) at $t = 100$ min, with the temperature set point 30 °C; then, temperature set point was decreased from 30 °C to 28 °C at $t = 200$ min (humidity ratio set point 24 g/kg). Fig. 12 illustrates the normalized controller outputs (normalized to maximum values). For this first simulation, the outside weather conditions are $T_{\text{out}} = 35$ °C and $w_{\text{out}} = 4$ g/kg (RH = 10%), while $S_i = 300$ W$\cdot$m^{-2}. The simulation results clearly demonstrate that noninteracting con-

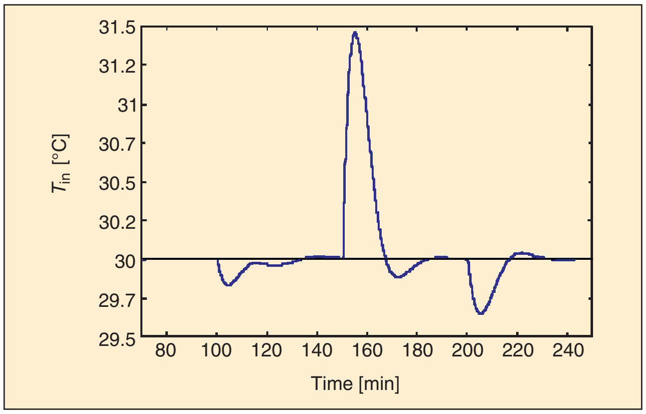

Figure 15. *Regulation of temperature T_{in} for step changes in external disturbances in case of uncertainty.*

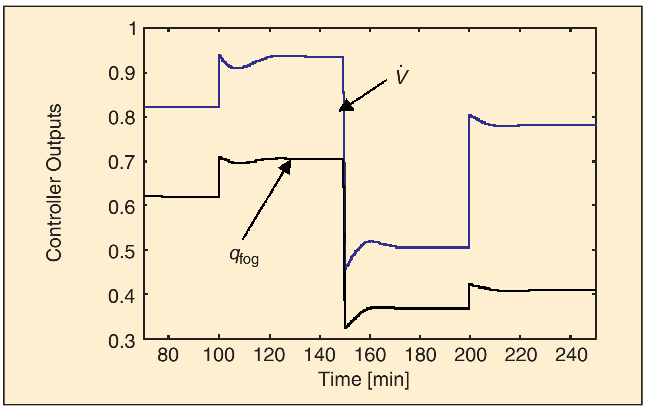

Figure 16. *Controller outputs for step changes in external disturbances in case of uncertainty.*

trol was attained and the closed-loop system response is acceptable.

A second simulation experiment demonstrates that closed-loop system response is not affected by weather conditions, since the feedforward term of the linearizing/decoupling controller compensates for external disturbances in the system. For this case, the desired set points are $T_{in,sp} = 30$ °C and $w_{in,sp} = 18$ g/kg. Step changes in disturbances were applied at $t = 100$ min (for S_i), 150 min (for T_{out}), and 200 min (for w_{out}). The step changes were: S_i from 250 to 300 W·m^{-2}, T_{out} from 35 °C to 32 °C, and w_{out} from 4 to 8 g/kg. With no uncertainty in the model parameters, weather conditions do not affect T_{in} and w_{in}, and controller outputs are depicted in Fig. 13. By adding a 10% uncertainty in system parameters, T_{in} and w_{in} become affected by weather conditions. However, the PD-0F controllers are able to provide fast regulatory control, as shown in Figs. 14-16. From this simulation, it is clear that the system remains decoupled and well behaved even with considerable parameter uncertainty.

Finally, simultaneous temperature and humidity control in a greenhouse was simulated using real weather conditions from a full summer day (3 June 1999) in Arizona, U.S.A. Set points for w_{in} and T_{in} were obtained as outputs of the PVT block (Fig. 3) and are illustrated in Figs. 17 and 18, together

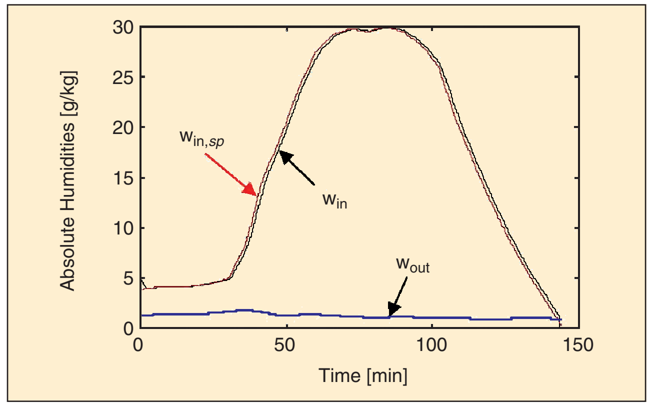

Figure 17. *Humidity ratio trajectories in case of simultaneous humidity ratio and temperature tracking.*

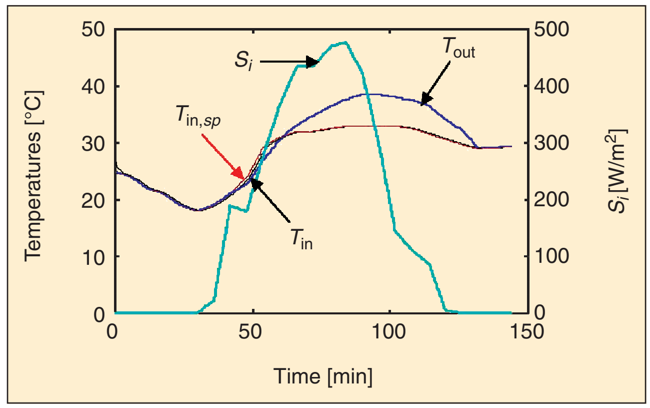

Figure 18. *Temperature trajectories in case of simultaneous humidity ratio and temperature tracking.*

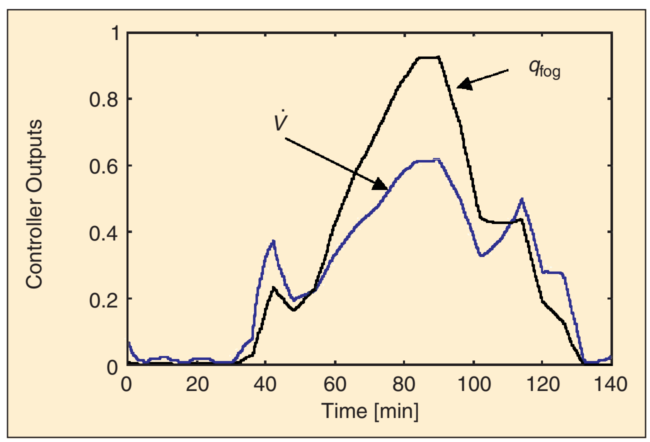

Figure 19. *Controller outputs in case of simultaneous absolute humidity and temperature tracking.*

with the trajectories of w_{in}, w_{out} and T_{in}, S_i, T_{out}, respectively. Fig. 19 illustrates the controller outputs for this case. The tracking performance of the proposed controller is excellent.

Summary and Conclusions

The advances in environment control methodologies experienced in the past few decades for plant cultivation are remarkable. We have described current research methodologies, including extending cultivation to space and off-planet systems, and provided a review of current research for the reader interested in the subject.

As shown in this article, the current art for control of aerial and root environments in plant culture accounts for the unique requirements of plants. These requirements include the need for protection from extremes in temperature, humidity, and radiation. A hierarchical decomposition of climate management demonstrates that several different time scales are pertinent to plant culture; thus, control engineers must consider these scales in system design. In general, plant cultivation in greenhouses and growth chambers is characterized by different optimization strategies, including minimization of direct costs, maximization of performance objectives, including biomass production or crop uniformity, and more recently model-based, supervisory, or knowledge-based control systems. Issues affecting control system implementation, including plant requirements and response to environment parameters, sensor design and use, and the need for a layered control implementation, were discussed.

An example of a coupled, nonlinear controller for greenhouse air temperature and humidity was developed. Simplifying methods were used to obtain a linearized, uncoupled control model with significant lag times in the two controlled variables. An example of tuning, utilizing PDF, was given, and the results of simulations of step changes in set points and disturbances, and the effect of parameter uncertainty, were explored. The simulations suggest that the resultant control system is robust, stable, and responds appropriately to disturbances and parameter uncertainties.

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The CONTROL CRYPTIC

Answer to last issue's Control Cryptic

1 W	I	2 N	D	3 O	W	4 S		5 M	A	6 P	S	
A		I		U		A		I		R		7 F
8 T	E	L	E	T	Y	P	E	S		9 O	C	R
T				L				O		P		I
	10 A	11 S	S	I	S	12 T	S		13 W	E	L	D
14 R		O		E		E		15 R		L		A
16 I	N	F	E	R	E	N	T	I	A	L	L	Y
C		T		S		S		B		E		S
17 A	W	L	S		18 D	E	T	O	U	R	S	
T		O		19 S				S				20 I
21 T	A	G		22 P	R	23 O	P	O	S	24 A	L	S
I		I		I		R		M		I		I
	25 S	C	A	N		26 S	T	E	A	R	I	C