Optimal Greenhouse Cultivation Control: Survey and Perspectives

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Abstract: A survey is presented of the literature on greenhouse climate control, positioning the various solutions and paradigms in the framework of optimal control. A separation of timescales allows the separation of the economic optimal control problem of greenhouse cultivation into an off-line problem at the tactical level, and an on-line problem at the operational level. This paradigm is used to classify the literature into three categories: focus on operational control, focus on the tactical level, and truly integrated control. Integrated optimal control warrants the best economical result, and provides a systematic way to design control systems for the innovative greenhouses of the future. Research issues and perspectives are listed as well.

Keywords: Optimal Control; Greenhouse Climate Control; Receding Horizon Control; Model Predictive Control; Dynamic Optimization.

NOTATION

$x \in \Re^{n_x}$	states	*Subscripts*	
$u \in \Re^{n_u}$	controls	g	greenhouse
$d \in \Re^{n_d}$	external inputs	c	crop
$y \in \Re^{n_y}$	outputs	o	outdoor
		e	equipment
f_F	partition factor	*Superscripts*	
H	Hamiltonian	nom	nominal
j	flux	sp, ref	set point
J	goal function	*	optimal
K	controller gain	obs	observed
L	running costs	s	slow
N	transformed co-state	f	fast
p_F	fruit price		
S	storage variables	*Other*	
W	biomass	^	estimate
z	auxiliary variables	{ }	trajectory
λ	co-states	¯	smooth approx.
Φ	terminal costs		

1. INTRODUCTION

Greenhouses act as a shelter for the crop. The ability to manipulate the conditions within the greenhouse enables control over crop production, thus allowing to boost productivity, to control quality, to have production of crops that otherwise would be impossible, and to prolong the cultivation period. In principle, the enclosure allows better crop protection and the use of less chemicals as compared to open field cultivation. Energy is needed for heating or cooling, and also water and nutrients, including CO_2, must be supplied from outside.

The consumer demand for price-worthy food and ornamentals on the one hand, and society concerns about sustainability, make it imperative to optimize greenhouse operations with respect to these goals. One consequence for control is that the target must be to exploit the sun as much as possible. Hence, the goal of control is not to suppress the effect of external signals, but to exploit them. Moreover, in order to achieve satisfactory results in view of the overall objective, it is not enough to just control the greenhouse climate, but the crop must be taken into account as well.

The frame of (economic) optimal control is most suitable to tackle the trade-off problems sketched above. Throughout this paper we take this frame as the leading paradigm, within which we place the various developments and proposals encountered in the literature and in practice, along the lines developed in Van Straten *et al.*(2010).

The objective of this contribution is (i) to provide a brief survey of the literature on greenhouse climate and cultivation control, (ii) to discuss the development of the various paradigms for optimal control, (iii) to discuss scientific challenges and perspectives for the future.

2. THE GREENHOUSE-CROP SYSTEM

2.1 Common core of greenhouse-crop systems

Fig. 1 shows the essential mass and energy fluxes that are generic to every greenhouse. Also the main information flows are shown.

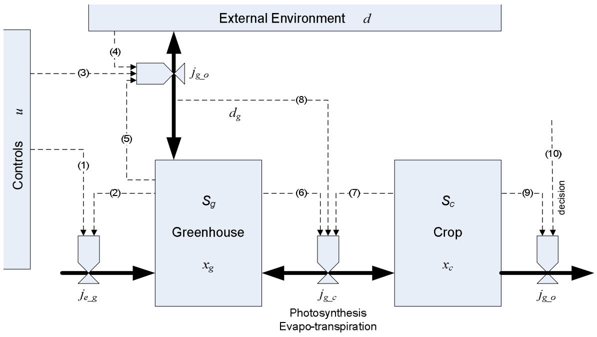

Fig. 1. Mass and energy fluxes in greenhouse system (solid lines) and information flows (dashed lines).

The grey rectangles denote the greenhouse and crop compartments, that have storage capacity. The stored energies and masses in greenhouse and crop are formally denoted here by the vectors S_g and S_c, respectively. The solid arrows denote fluxes j of energy, water or carbonaceous material.

The masses and energies S_g and S_c are extensive variables, that can easily be coupled to intensive variables such as concentrations or temperatures. The intensive variables are indicated formally in the scheme by the state vectors x_g and x_c for greenhouse and crop, respectively.

The dashed arrows indicate by which variables the fluxes are influenced. They can be seen as information flows. The control inputs u directly affect the fluxes between equipment and greenhouse j_{e_g} (shown as flux *1* in Fig. 1), such as the opening of the heating valve and the valve for CO_2-supply, for instance. However, the actual flux may also depend upon the state of the greenhouse (*2*). The heat input flux, for instance, is not a unique function of the position of the heating valve, but also depends upon the greenhouse temperature (and, in fact, the direct radiation received by the heating pipes; not indicated in the figure).

The flux between the greenhouse air and the outdoor environment j_{g_o} consists of various components. Water and CO_2 are exchanged via ventilation, and heat is exchanged via radiation, ventilation and transport through the walls. The window opening is a control (*3*), but as the ventilation flux at a given window opening also depends upon the wind speed, there is also a dashed arrow from the environment (*4*). Similarly, the radiation flux through thermal screens is not only controlled by the opening of the screens (i.e. u , signal *3*), but also by the outdoor radiation received (*4*). Clearly, the moisture, CO_2 and heat exchanged depend upon the concentrations of water vapour, CO_2 and the temperature (*5*).

The exchange between greenhouse internal environment and the crop (j_{g_c}) comprises the CO_2 uptake by photosynthesis, the CO_2 release by various forms of respiration, and the release of water by evapo-transpiration. They depend upon the greenhouse states (*6*) as well as the crop states (*7*), and also, indirectly, upon the environment, *in casu* the solar radiation (*8*). This is expressed in the scheme by the direct throughput d_g. By means of screening or artificial lighting it can be manipulated, and hence have a direct influence on the greenhouse-crop fluxes. Otherwise the greenhouse-crop fluxes cannot be manipulated directly, except by measures not related to the greenhouse climate, such as watering and application of growth regulating chemicals. Crop harvest is part of the flux j_{c_o} as well as the discrete decision actions of picking leafs and pruning, etcetera (*10*). The resulting fluxes obviously depend upon the state of the crop (*9*).

Relevant to controller design is that the controllable fluxes have constraints that are not only determined by the installed capacity, but also by the environmental conditions and the system variables. The ventilation flow is an example, as at maximum window opening, the actual flow still depends on wind speed and greenhouse temperature. Similarly, the maximum heat flow from heating pipe to greenhouse is not fully defined by maximum valve opening, but also depends on the temperature difference between boiler temperature and greenhouse air temperature. Hence, most controllable fluxes have time-varying constraints.

The figure also reveals the pivot role of the biophysical processes, i.e. photosynthesis, respiration and evapo-transpiration. They respond in seconds to changes in external conditions, in particular the light.

2.2 State-space modelling

Proper design of (optimal) controllers require a dynamical model of the system. The dynamics of the combined greenhouse-crop system can be represented by the following general state-space description:

$$\begin{aligned} \dot{x}(t) &= f(x(t), u(t), d(t)) \\ y(t) &= g(x(t), u(t), d(t)) \end{aligned} \tag{1}$$

where *x(t)* is a vector of system states (e.g. air temperature, air moisture content, air CO_2-concentration, assimilate carbon content of the crop, structural carbon content of the crop, fruit weight), *u(t)* a vector of control inputs (e.g. heat input or mixing valve position, window opening, CO_2-supply rate, screen position), *d(t)* a vector of external disturbances (e.g. solar radiation, outside air temperature, outside CO_2-concentration, wind speed), and *y(t)* a vector of outputs (e.g. air temperature, relative humidity, crop dry and fresh weight). The functions f and g are vector valued functions, of dimensions n_x and n_y, respectively, where f specifies the rate of change of the states, and g how the output variables of interest depend upon the states and the inputs.

2.3 Hierarchy

Motivated by heuristic arguments related to the time-scale decomposition discussed below, the control by modern computerized control systems has a hierarchical structure as depicted in Figure 2. On the basis of experience and visual observations on the crop the grower conveys operational settings to a supervisory management system. This component combines information on nominal climate conditions, i.e. day or night, time of year, with cultivation schedules into information to be used by the actual feed-back controller. The controller is fed by actual measured sensor outputs $y_g^{obs}(t)$, and in some more advanced cases, sensor information on the crop, e.g. evapo-transpiration, may be available as well. The controller returns command signals for the actuators. Sometimes, the driving signal to the actuator is a command signal to an embedded lower level local controller (e.g. flow controller or a pipe temperature controller).

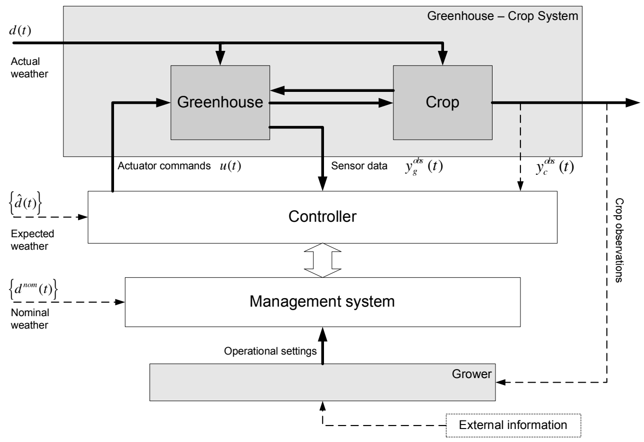

Fig. 2. Control hierarchy.

Computerized control is an intrinsic part of present day modern greenhouses (cf. Bakker *et al*. 1995). The functions of a current hierarchical climate computer can be summarized as follows:

1. it takes care of realizing a suitable protected environment despite fluctuations of external weather (controller function, operational level on scale of minutes),
2. it acts as a program memory and supervisory layer, which can be operated by the grower as a tool to steer his cultivation (supervisory function, tactical level on longer time scales).

2.4 Current status of computerized control

The controller algorithms in current climate computers often have been designed in a heuristic way, starting from switching rules for heating and ventilation supplemented with single loop proportional controllers. Temperature control, humidity control and carbon dioxide control interact, in a way that is not constant but is depending on whether the system is in heating or cooling mode. Moreover, a set of decision rules is needed to resolve conflicts between the temperature and the humidity controller, since the ventilation actuators serve to release surplus heat as well as surplus moisture. In order to leave room for the controllers, usually there is an operation band, which can be defined by the grower. On top of this, automatic adaptations are made, in order to allow higher temperatures when the solar radiation is higher. The grower can adjust all these settings. Also, he decides on risks of condensation of moisture on fruits, or on overheating of plants, by setting constraints to humidity, or by operating a fog system. Finally, the main algorithm can be overruled by safety considerations, e.g. in the case of rain or thunderstorms.

Although highly successful, the computer systems in use today leave much to be improved (cf. Challa and Van Straten 1991). First, from the point of view of low-level controller performance, it is unlikely that desirable characteristics, such as overshoot, rise time, suppression of oscillations, and off-set, can be handled in a systematic and insightful way in the heuristic rule-based assembly of separate loops found in today's controller programs. Second, the computer's function as a memory for programmable trajectories introduces a very large number of user adjustable settings to define them. Modifications in trajectory definitions have a definite effect upon the energy and other resources consumption, as well as on the growth and development of the crop, but the exact effect is unknown to the grower, and is only inferred from experience. Third, despite current energy management overlays, there is little information about the economics of the operation, and about the grower accessible factors that determine the economics. If a grower is making changes in settings, the consequences for the process and its economy are essentially unknown.

In principle, the best way to remedy the situation is to compute at any time control actions that optimize the ultimate (economic) goal function of the user, given the actual and forecasted weather, and the currently observed state of the greenhouse and crop. This is known as optimal control. It serves as a basic framework that can help to classify the various control paradigms proposed in the literature. In the next section we first briefly present the optimal greenhouse-crop control problem in formal mathematical terms.

3. OPTIMAL CONTROL

3.1 Mathematical formulation

Optimal control is achieved by solving the following problem. Given the system (1) with initial state $x(t_o) = x_o$ plus additional auxiliary output variables of interest

$$z(t) = h\big(x(t), u(t), d(t)\big) \tag{2}$$

find the control trajectory

$$u(t), t_o \le t \le t_f \tag{3}$$

that minimizes the goal function

$$J\left(u(t),t_o,t_f\right) = \Phi\left(x(t_f),t_f\right) + \int_{\tau=t_o}^{\tau=t_f} L\left(z(\tau)\right)d\tau \tag{4}$$

subject to the additional inequality constraints

$$c\left(x(t),u(t),d(t)\right) \le 0, \quad t_o \le t \le t_f\,. \tag{5}$$

The constraint conditions refer to input constraints, defined by the operating range of the actuators; state constraints, such as maximum allowable temperatures; output constraints, such as maximum allowable relative humidity. Note that the consideration of state and output constraints would not be necessary if the models were accurate over the entire space domain of interest. If, for instance, a high temperature would be detrimental to the crop, and this phenomenon were correctly captured in the models, then the optimal control algorithm would automatically avoid that high temperatures occur.

The variables of interest *z(t)* are, in fact, ordinary outputs that just like the customary outputs *y(t)*, can be computed from the states, control inputs and external inputs, but without having a counterpart in the actually observed variables $y^{obs}(t)$. Examples of observational model outputs *y(t)* are temperature or relative humidity, for which sensors are available. Examples of variables of interest *z(t)* are the heating rate or the ventilation rate, for which usually no direct measurements are available. From a mathematical point of view their introduction is not strictly necessary, but they are used here for convenience and because of their role in practical implementations.

3.2. Solution method and dream pattern

A particular powerful solution method involves the formation of the Hamiltonian

$$H\left(x,u,\lambda,d\right) = L\left(x,u,d\right) + \lambda^T f\left(x,u,d\right), \quad t_0 \le t \le t_f \tag{6}$$

where λ are the adjoint variables or co-states, subject to

$$-\dot{\lambda} = \left(\frac{\partial H}{\partial x}\right)^T, \quad t_o \le t \le t_f\,, \quad \lambda(t_f) = \left(\left.\frac{\partial \Phi}{\partial x}\right|_{t=t_f}\right)^T, \tag{7}$$

and requiring that

$$\frac{\partial H}{\partial u} = 0, \quad t_o \le t \le t_f \tag{8}$$

This method transforms the original problem of finding the optimal control trajectory by maximizing J over the full horizon to maximizing, at every time, the Hamiltonian with respect to the actual control. In cases where u hits an upper or lower bound, condition (8) is replaced by choosing the bound where H is maximum, according to Pontryagin's maximum principle. It has to be noted that stationarity condition (8) leads to locally optimal solutions, but not necessarily to solutions that minimize J globally (Stengel 1994).

Performing the optimization leads to the optimal trajectories over the period $t_o \le t \le t_f$ of the controls $u^*(t)$, the state $x^*(t)$, the co-state $\lambda^*(t)$, as well as the goal function evolution

$$J^*(t) \equiv J\left(u^*(t)\right), \quad t_o \le t \le t_f \tag{9}$$

with ultimate value $J^*(t_f)$. It should be noted that even if no use is made of a solution method that involves co-states, the co-state can still be computed afterwards.

If the models were exact, and the weather would be known in advance, these computations can be done without the need for any additional data except for the initial conditions. Using the real external weather will yield the best achievable control pattern, but, obviously, this 'dream pattern' can only be computed *a posteriori*.

3.3 Time scale decomposition

In reality, the weather is not known in advance, and will deviate from the assumed weather. Hence, the open loop solution cannot be used directly on-line. However, the fact that the crop biomass has slow dynamics, and the physics of the greenhouse (including the crop bio-physics) have fast dynamics, allows a time-scale decomposition

$$\dot{x}^s(t) = f^s\left(x^s(t),x^f(t),u(t),d(t)\right) \tag{10}$$

$$\dot{x}^f(t) = f^f(x^s(t),x^f(t),u(t),d(t)) \tag{11}$$

where x^s and x^f are the fast and slow states and f^s and f^f represent the fast and slow modes. The fast processes also comprise the bio-physical processes in the middle of Fig. 1. This time-scale decomposition offers the opportunity to separate the problem in two stages (cf. Van Henten and Bontsema 2009).

3.4 Off-line dynamic optimization (slow problem)

First, the following slow sub-problem is solved off-line. A nominal input trajectory $d^{nom}(t)$, derived from long term history, is chosen, and the greenhouse is assumed to be pseudo-static:

$$\dot{x}^s(t) = f^s\left(x^s(t),x^f(t),u(t),d^{nom}(t)\right) \tag{12}$$

$$0 = f^f(x^s(t),x^f(t),u(t),d^{nom}(t)) \tag{13}$$

The original dynamics of the greenhouse (11) act as a filter, that filters out very high frequencies, whereas Eq.(13) has no filtering properties. Therefore, in evaluating (13) the input signals must be smooth, as otherwise one would get unrealistic high frequencies in the fast system states.

The result of the calculation are trajectories for the optimal controls, slow states and co-states, i.e.

$$\bar{u}^*(t), \bar{x}^{s*}(t), \bar{\lambda}^{s*}(t), \quad t_o \le t \le t_f \tag{14}$$

where the overbar indicates that the solution is an approximation that holds for the smooth nominal input. The slow problem can be computed off-line in advance.

3.5 On-line optimal control (fast problem)

The controls cannot be used directly on-line, as the real weather deviates from the nominal one. Therefore, feed-back must be provided. There are two major pathways to achieve a practical on-line controller. These are:

1. use the output trajectories as set-point to low level controllers. This is the usual hierarchical scheme as encountered in industry, and it is the dominant approach in the greenhouse control literature (Fig. 3),
2. use the slow co-state as shadow prices and repeatedly solve on-line an optimal control problem, based on the same economic goal function as used on the level of the slow sub-problem, but over a shorter horizon. This leads to a receding horizon optimal controller RHOC (Fig. 4).

Both approaches can be seen as hierarchical solutions, in the sense that there is a de-coupling between off-line calculations and on-line control. The connection is more tight in the second solution, which may therefore better be called 'decomposed' optimal control. The different way in which information is transferred from the slow to the fast problem can clearly be seen from the figures.

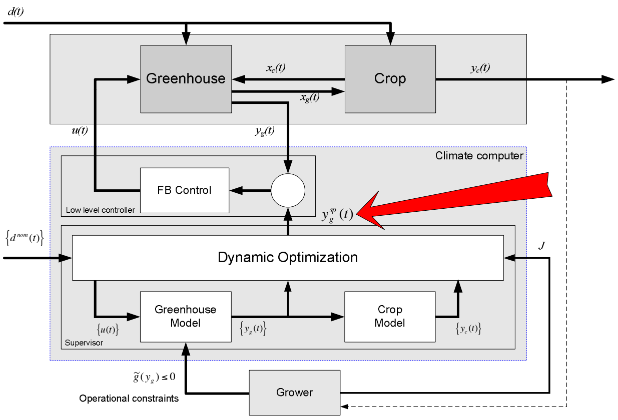

Fig. 3. Focus on dynamic optimization. Generation of optimal set point trajectory.

The goal function of the receding horizon optimal controller is

$$J^f\left(u(t), t_s, t_s+h\right) = \int_{\tau=t_s}^{\tau=t_s+h} \left(L\left(\bar{x}^{s*}, x^f, u, \hat{d}\right) + \bar{\lambda}^{s*T} \frac{\partial x^{s*}}{\partial t} \right) d\tau \tag{15}$$

where the control is computed from the current sampling instant t_s over the horizon $t_s + h$. In (15) the approximate trajectory of the smooth states are used to calculate the running costs L, and the optimal slow co-state $\bar{\lambda}^{s*}$ acts as an instantaneous price for a rate of increment of the slow state (biomass), which can be evaluated at the actual conditions. The external inputs are obtained from a short term weather forecast $\hat{d}(t), t_s \le t \le t_s + h$.

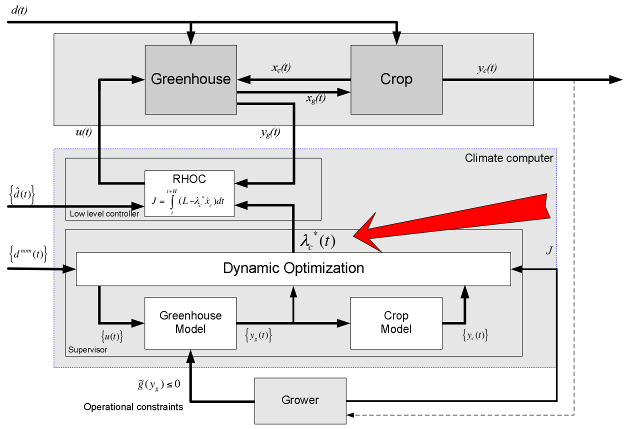

Fig. 4. Integrated optimal control. Transfer of strategic information via crop co-states. Receding horizon optimal control on the operational level, using the same economic goal function plus weather forecast.

4. CONTROL PARADIGMS

On the basis of the overview of the optimal control methodology above, we are now ready to classify the various contributions proposed in the literature. We use the hierarchy/decomposition in two levels as major guideline. The following major categories are distinguished.

1. References that focus on the fast time scales, i.e. on-line control of the greenhouse climate. This approach is related but not necessarily equal to the fast sub-problem in optimal control.
2. References that focus on the slow time scale, i.e. generating control strategies motivated by the behaviour of the crop. This approach is related but not necessarily equal to the slow sub-problem in optimal control.
3. References that discuss both levels in an integrated fashion. This approach is related but not equal to the full optimal control problem.

Within each category a further distinction can be made between solutions without and with economic optimization considerations. In each category, there are many variants, which depend upon (i) the degree in which the solution accommodates or exploits common attributes of greenhouse-crop cultivation systems, (ii) differences in situation, e.g. type of crop or special economic constraints, (iii) differences in methodology (model type, optimization method).

4.1 Focus on feedback control of fast processes

The idea of feedback control is to maintain or satisfy given conditions that are supposed to be favorable to the crop. Acceptable operational set-point or upper and lower bound trajectories are defined by a number of definition points in time, called settings. To the controller it is immaterial how the settings are derived, be it as the result of dynamic optimization, or as 'blue prints' derived from practice. Since the crop is not part of the control system, the economic result depends to a large extent upon how the settings are chosen. Unless additional tools are provided, such as simulation aids or balance calculations, there is no clue about the extent of effects of settings changes. In the realization of the desired trajectories by the controller, there is no trade-off between benefits from selling the crop and operational costs. In this approach, the problem is reduced to a (multi-variable) controller design problem. Hence, the full machinery of controller design theory can be used to design a controller.

4.1.1 Realizing a given greenhouse climate

PI control

Early designs of PI control on the basis of experimentally obtained transfer function models has been described e.g. by Udink ten Cate (1987). In commercial nurseries, P- or PI-control is commonly used in the control of greenhouse heating pipe temperature, which is part of cascade control of greenhouse air temperature.

Forward compensation, Pseudo-derivative Feedback

Using models, it is also possible to provide feed-forward compensation (e.g. Udink ten Cate 1987). To cope with the inertia of the actuator system, and also with time delays in the loop, pseudo-derivative feedback with load compensation has been proposed by Setiawan, Albright, and Phelan (2000).

Decoupling and feedback linearization

Boulard and Baille (1993) linearize the heat and vapor balances to obtain linearized equations that allow to take into account the coupling between these systems due to ventilation and fogging. Decoupling between temperature and CO_2 loops is achieved by Linker, Gutman, and Seginer (1999), where temperature is controlled in a loop with the ventilation, and the CO_2 loop is conditional upon the achieved ventilation rate.

The greenhouse dynamics is bi-linear with respect to the ventilation rate as control. By writing the (scalar) system in the mixed linear/non-linear control affine form

$$\dot{x} = ax + f(x) + b(x)u \tag{16}$$

and by defining a virtual model-based control u' via

$$u = \frac{u' - f(x)}{b(x)}, \quad b(x) \neq 0 \tag{17}$$

a system is obtained that is linear in the virtual control, and any linear controller design methodology can be used. This method was proposed for ventilation control by Berenguel et al. (2006). A multivariable case including psychrometric constraints is presented by Pasgianos et al. (2003). They also give an extensive account on coupling issues and constraints related to the psychrometric properties. The same treatment can also be found in Albright et al. (2001).

State or output feedback multivariable control

A state feedback controller takes the closed form, in discrete time, of

$$\delta u(t_k) = -K\delta x(t_k) \tag{18}$$

where $\delta x(t_k) = x(t_k) - x^{ref}(t_k)$ and $\delta u(t_k) = u(t_k) - u^{ref}(t_k)$ are deviation variables from a trajectory that satisfies the state equation $\dot{x}^{ref}(t) = f\left(x^{ref}(t), u^{ref}(t), d^{ref}(t)\right)$, and K is a gain matrix. By implementing (18) in incremental form, and ignoring changes in reference values over a control interval, the reference trajectories are not explicitly appearing anymore, i.e.

$$u(t_{k+1}) = u(t_k) - K\left(x(t_{k+1}) - x(t_k)\right) \tag{19}$$

The gain matrix K can be designed by pole placement or by minimizing a quadratic error (Linear Quadratic designs). An application to greenhouse control is proposed in Van Henten (1989).

State reconstruction is usually not used in greenhouse climate control, as the current states have more or less direct counterparts in the measured variables. However, sensor info from a specific location may not be sufficiently representative for spatially averaged variables in a lumped model, so there could be a case for state estimation. State reconstructors have been proposed e.g. in the 1998 reference quoted in Piñón et al. (2005), and in Speetjens, Stigter, and Van Straten (2009).

Proportional-Integral-Plus control (PIP)

This special class of PI controllers derives from the True Digital Control (TDC) philosophy originating from Young and co-workers Young et al. (1987). Input-output models are set-up directly in sampled data space as a discrete time ARMA (auto-regressive moving average) model of the form

$$\begin{aligned} y(k) = {} & a_1 y(k-1) + a_2 y(k-2) + \ldots + a_n y(k-n) + \\ & b_1 u(k-1) + b_2 u(k-2) + \ldots + b_m u(k-m) \end{aligned} \tag{20}$$

where u and y are defined as deviation variables. Next, a state vector is defined as

$$\begin{aligned} x(k) = [\, & y(k) \;\; y(k-1) \;\cdots\; y(k-n+1) \;\ldots \\ & u(k-1) \;\cdots\; u(k-m+1) \;\; z(k)] \end{aligned} \tag{21}$$

where $z(k)$ is an integral of error term

$$z(k) = z(k-1) + \left(y_d(k) - y(k) \right) \quad (22)$$

with $y_d(k)$ the reference value. This term is provided to cope with off-sets due to load variations, as is also customary in ordinary PI controllers.

With (21) and (22), (20) can be written in non-minimal state space form as

$$x(k) = Fx(k-1) + gu(k-1) + dy_d(k) \quad (23)$$

where the matrix F and the vectors g and d are composed of the coefficients of (20). The controller then follows as a standard state feedback controller according to (18).

This approach has been applied to a scale model of Nutrient Film Technique, NFT, (Young, Tych, and Chotai 1991), to free air carbon dioxide enrichment systems (Lees et al. 1998), and to carbon dioxide enrichment in open top chambers (Taylor et al. 2000). Young et al. (1994) describe an application for greenhouse temperature control, and also describe a multivariable expansion to control relative humidity and CO_2 as well. Preliminary results were reported that show that RH can be controlled within $\pm 3\%$ and temperature to within ± 0.5 ^{o}C.

Robust control

Robust control has been proposed for greenhouses by Bennis et al. (2008). The designer must set the expected uncertainty bounds in the system's responses in the frequency domain, or, alternatively the parameter uncertainty may be formulated explicitly (Linker, Gutman, and Seginer 1999). Robust controllers are intended to work in a stable fashion over a wide range of actual operation points, but such designs tend to be conservative, especially in situations like a greenhouse, where variability in external inputs could be exploited.

Adaptive control

Another answer to uncertainty is provided by adaptive control. Application to greenhouses are reported by Young et al. (1987), Arvanitis, Paraskevopoulos, and Vernardos (2000), Rodríguez et al. (2008), Speetjens (2008).

Model predictive control (MPC)

MPC uses the model to predict the output in the (near) future, and then finds the pieces-wise constant control trajectory that optimizes at each actual discrete time instant t_k

$$J\left(u(t_k),..u(t_{k+M-1})\right) = \sum_{j=k+1}^{k+N} \left(\left(\hat{y}(t_j) - y^{ref}(t_j) \right)^2 + \beta \Delta u(t_j)^2 \right) \quad (24)$$

where $M < N$ is the control horizon, N the prediction horizon, $\hat{y}(t_j)$ the predicted output vector at future times t_j, $y^{ref}(t_j)$ a desired reference trajectory, $\Delta u(t_j) = u(t_j) - u(t_{j-1})$ is the control move. The factor β is a design parameter that weighs the relative importance of tracking error versus control effort. Feed-back is provided because the prediction starts from the current state (estimate). Only the first calculated control is applied to the system, after which the cycle is repeated at the next time instant (Richalet et al. 1978).

MPC can be seen as a special case of optimal control, where the goal function has the quadratic form of (24). It provides solutions that are optimal from the point of view of control performance, but this is not necessarily optimal in an economic sense. MPC can deal with constraints on inputs and outputs, but in that case no closed solutions can be found, thus introducing the need for on-line optimization. In that case MPC takes the form of a receding horizon controller. Greenhouse applications have been reported by El Ghoumari, Tantau, and Serrano (2005), Piñón et al. (2005), Ramírez-Arias et al. (2005), Berenguel et al. (2006) and Blasco et al. (2007).

Multi-objective control

Using quadratic cost functions for each single loop for heating, fogging and ventilation turns the problem into a multi-objective control problem. Within the operational bounds, a Pareto front is obtained. As, ultimately, only one single control must be applied, a selection is made on economic grounds, for instance lowest energy costs (Xu, Hu, and Zhu 2009), net benefit (Zhang 2008), or a control performance weighing (Hu, Xu, and Hu 2009).

4.1.2 Greenhouse climate control with cost minimization

Although economics is often given as motive to design the advanced controllers described in the previous sections, economics is not explicitly included, and there is no guarantee that the economically best result is, indeed, achieved. In stead of designing the controller on the basis of pure control criteria, control solutions have been proposed were the controller does have an economic goal function.

Minimizing costs within operational bounds

Basically, in this approach a new optimal control problem is formulated, with crop demands as constraints, and cost of energy and other resources as part of the goal function. There are no states associated to the crop. Some authors use the Hamiltonian approach to solve the resulting optimization problem. The usual way of thinking is to try to save energy (Bailey and Seginer 1989; Marsh and Albright 1991b) or to minimize CO_2 costs (Challa and Schapendonk 1986; Ioslovich et al 1995; Seginer et al. 1986), i.e. to minimize costs, while satisfying conditions related to crop yield. The long term crop aspects are covered by blue-prints and the like. Gutman et al. (1993) building on Seginer (1988) uses the Hamiltonian approach to strive for minimization of heating costs by exploiting deviations allowed from the standard blue prints expressed in temperature sums, based on perfect weather conditions. The result is a non-linear MPC. Assuming that a value is attached to the photosynthetic rate, Trigui, Barrington, and Gauthier (2001) propose to use the Hamiltonian approach to optimize a short term goal function with co-states for the fast variables.

Partial solutions: CO_2 enrichment

CO_2 enrichment has been one of the earliest applications of optimal control. This involves balancing the cost for CO_2 supply against the benefit of increased photosynthesis. Solutions are based on instantaneous optimization (Challa and Schapendonk 1986; Critten 1991; Van Meurs and Van Henten 1994), or consider dynamics and light or photosynthesis integration (Chalabi 1992; Ioslovich et al. 1995; Ferentinos, Albright and Ramani 2000; Chalabi et al 2002a). Model-based control to ambient CO_2 without economics is described by Kläring et al. (2007).

Partial solutions: thermal screens

Operation of thermal screens based on a trade-off between energy savings versus instantaneous loss of due to the light intensity reduction is briefly described in Bailey (1988) and Bailey and Chalabi (1994). The optimum is obtained by simulation. Seginer and Albright (1980) find the break-even point by equating the rate of cost savings of heat loss prevention due to closing the curtains to the rate of cost increase due to prolonged production time.

4.1.3 Exploiting the integrating capacity of the crop

Temperature integral

This approach assumes that the requirements of the crop can be expressed in terms of integrals over time, similar to the degree-days concept in open field crops. Lower temperatures can be compensated by higher ones at a later time, which then can be used to achieve cost savings. Seginer, Gary, and Tchamitchian (1994) present a detailed analysis to confirm this based on a crop model.

Shifting some of the heating during the day to periods with low wind dependent losses is described by Bailey and Chalabi (1994). Based on this, Chalabi, Bailey, and Wilkinson (1996) published an algorithm to achieve running 24 hours temperature integral within constraints set by the grower, using weather forecasts. In the same class belongs optimal use of daily heat storage buffers, which allow to decouple heat demand from heat supply and flue gas CO_2 use (e.g. Chalabi et al. 2002b). Other studies on minimizing resources are found in Lacroix (1999), Sigrimis, Anastasiou, and Rerras (2000), and Körner and Challa (2003). Gutman et al. (1993) solve a 96 hour temperature integral problem with linear programming and present an in-depth analysis of the solution using co-states and Pontryagin's maximum principle.

Light integral

Albright, Both, and Chiu (2000) produce a contracted amount of lettuce heads of a specific weight per unit time by maintaining at constant temperature a daily light integral, using supplementary lighting. Further developments of this idea are reported by Ferentinos, Albright, and Ramani (2000) and by Seginer, Albright, and Ioslovich (2006).

4.1.4 Controlling fast crop processes; the "speaking plant".

In stead of set-points or short term integral values, one could also consider the fast physiological crop processes as the to be controlled variable. This is also known under the name "speaking plant" concept (Udink ten Cate, Bot, and Dixhoorn 1978). The main motivation given to control crop related rates is to prevent undesired crop developments, and to satisfy quality requirements. The settings, however, are based on heuristics.

An early application is described by Hashimoto (1980), who proposes to use the electrical capacitance of the stem and the leaf temperature as indicators of the short term plant *growth rate*. An interpretation of the concept from different perspectives is given in Hashimoto (1989). In an experiment on *transpiration control* Stanghellini and Van Meurs (1992) argue that a "minimal" rate of transpiration must be sustained to prevent the effects of calcium deficiencies, such as blossom end rot in tomato. Schmidt (1996) presents heuristic control rules in combination with an adaptive model to control leaf temperature and to keep plant evapo-transpiration within specific bounds. The difference between air temperature and canopy temperature measured by an infra-red sensor as indicator of crop behaviour was controlled in Langton et al. (2002). An evapo-transpiration related control method to prevent Ca-deficiency, plant water stress, and airborne fungal diseases in Chrysanthemums was described by Körner and Challa (2004). The idea that control can be used to reduce pesticide use is also elaborated in Tantau and Lange (2003).

The IntelliGrow system described in Aaslyng et al. (2003) tries to control the *photosynthetic rate* at 80% of the maximum attainable rate, and selects temperature and CO_2 set-points which yield the lowest energy input.

Assimilate balance

An analysis by Van Straten (1999) suggest that temperature integral and light integral should be coupled to prevent surplus or shortage of assimilates. In real greenhouses this happens inadvertently by poor control, showing that precise control is not per se desirable. In elaborate models for tomato and sweet pepper Elings et al. (2006) confirm the principle of maintaining the source-sink balance, resulting in a correlation between daily temperature set point and light sum. An attempt to control the instantaneous assimilate balance using the measured ratio of leaf length and stem diameter in tomato seedlings is described by Morimoto and Hashimoto (2000).

4.2 Focus on strategies driven by slow crop processes

Here the crop is central, and the main purpose is to derive 'strategies' that can be imposed on the greenhouse climate control. These are either derived by expert rules, or by slow sub-system optimization (section 3.4 As the focus is on the crop, the greenhouse is incorporated only to obtain an estimate of the expected cost of operation.

4.2.1 Assessing economics by simulation or local optimization

Jones, Jones, and Hwang (1990) use TOMGRO to derive approximately optimal set-points for tomato by simulation. SUCROS was the model used by Marsh and Albright (1991a), Marsh and Albright (1991b), to derive daily average set-points for hydroponic lettuce. Seginer and Sher (1993) also find set-points using TOMGRO. In their approach future operational costs are not influenced by the decision for the day so that the series of set-points can be found by the so called Sequential Control Search (SCS). A numerical analysis for lettuce in Seginer and McClendon (1992) suggest that this simplified SCS approach gives about the same state trajectories as the full slow problem. An empirical regression type crop model is used by Alscher, Krug, and Liebig (2001) to select the optimal temperature and CO_2-concentration out of a set of pre-defined day/night temperatures and CO_2 set-points. The economic result may be biased as in all these studies humidity was not taken into account.

4.2.2 Optimal strategies using dynamic optimization

One of the earliest contributions in this category is described in Seginer (1980). Central to the approach is the assertion that in each stage of crop development biomass increase can be written as

$$\frac{dW}{dt} = G(z)g(W) \tag{25}$$

i.e. as a product of a term $G(z)$ that is a function of greenhouse conditions only, and a term that depends only on the biomass. $G(z)$ is equal to the relative growth rate as observed in early stages of crop growth, when $g(W)=W$, and to absolute growth rate at mature stages, where $g(W)=1$. The vector $z=[x^f(u,d)\ \ d]^T$ represents the crop environmental conditions inside the greenhouse, e.g. temperature, light intensity, etcetera. The time needed to realize a desired biomass increment from W_A to W_B can be deduced from the equality

$$\int_{W_A}^{W_B} \frac{1}{g(W)} dW = \int_{t_A}^{t_B} G(z)dt \tag{26}$$

If the desired biomass increment is fixed the left hand side is a known constant γ. Hence, any change in greenhouse states leads to a different harvest time, which is supposed to generate costs due to space usage, and also can give losses or benefits in relation to time of delivery at the market. The net costs (benefits) must be balanced against the cost of operating the equipment, i.e. the cost needed to keep the pseudo-static greenhouse at the desired trajectory of $z(t)$. The basic methodology along this line of thoughts has been worked out further in Gal, Seginer, and Angel (1984). This is perhaps the first paper that introduces the idea of a Lagrange multiplier in greenhouse climate control, which has its equivalent in the dynamic co-state of optimal control with fixed final time. It is shown that the Lagrange multiplier λ represents the marginal cost worth paying for an additional unit of growth rate. The proposed control methodology has been applied in a simulation study for optimal CO_2 enrichment in Seginer et al. (1986). The separation of the basic crop model as independent products as in (25) was also used by Chalabi (1992) for the same purpose.

In a later paper, Seginer (1989) extends the case of fixed final state and variable final time to the optimal cultivation of tomato seedlings. It was shown that when the grower is constrained by area, it makes sense to apply a higher intensity of cultivation, i.e. heating and CO_2 dosage, when the market price is higher. The idea of the product breakdown of (25) was further developed for a two-stage crop in Seginer and Ioslovich (1998), with continuous harvest in the second, generative, stage. It can be shown that the Hamiltonian takes the form

$$H = NG(z) - L(u) \tag{27}$$

N is called a transformed co-state, defined by

$$N = (\lambda + p_F f_F)g(W) \tag{28}$$

where f_F is some function of biomass or time, expressing which fraction of the biomass produced is going into fruit, and p_F the price of fruits. In the vegetative period, when f_F is zero, the transformed co-state is the product of the original co-state $\lambda(t)$ and the biomass dependent term $g(W(t))$, that is associated to leaf area index. It was shown that, during this period, N is constant. A constant N implies that the co-state itself varies (decreases) over time when the canopy closes. This confirms the results found numerically by Van Henten (1994) for lettuce. A constant N also implies that when the vegetative biomass does not increase anymore (i.e. $g(W) \approx 1$), the co-state would depend upon the fraction of biomass that is allocated to the fruits. Indeed Van Straten, Van Willigenburg, and Tap (2002), found that in the generative stage of a tomato crop under realistic weather conditions the co-states vary over the season. The assertion of Seginer and Ioslovich is that the transformed co-state, being essentially constant, may be a better candidate to transfer long term information to the daily control than the co-state itself. Ioslovich, Gutman, and Linker (2009) expand the idea to a three-stage description of tomato growth into a vegetative, mixed vegetative-generative and generative stage. As in Seginer and Ioslovich (1998) part of the analysis deals with the transition between stages. Ultimately, the transition depends on the number of accumulated effective degree-days. The model parameters are derived from comparison with the calibrated TOMGRO model. They propose to use the optimal N as a basis for on-line control, but no details are given. The idea is also put forward by Seginer (2008), who coins the term “cultivation intensity” to denote the transformed co-state.

4.2.3 Other studies on the nature of co-states and optimal control solutions

Co-state trajectories for a two-state lettuce crop, where the states are biomass and leaf area ratio, using smoothed nominal synthetic periodic weather, are presented by Seginer et al. (1991). Results suggest that in the beginning it makes sense to achieve canopy closure as soon as possible. Van Henten and Bontsema (1991) and Van Henten (1994) also compute optimal temperature and CO_2 trajectories for lettuce cultivation, both with single state (biomass) or two state (structural and non-structural biomass) crop models. The computations revealed that the optimal temperature and CO_2 profiles with real weather are strongly fluctuating as compared to a calculation based on long-year averages, although the trend is similar. All co-state trajectories show a decreasing trend towards zero in about 20 days, equally suggesting that initial investment in dry matter production is worthwhile. This amounts to on average higher greenhouse temperatures at the beginning of the growing season, and lower ones later on, consistent with the findings of Seginer et al. (1991). As shown by De Graaf (2006) in a study on optimal control of nitrate in lettuce, the actual optimal on-line greenhouse temperatures are fluctuating quite heavily throughout the season, as driven by the actual weather, which is consistent with the findings of Gal, Seginer, and Angel (1984), who state that the temperature set-point should depend on the actual weather only. Even though this may be the case, the results of Seginer et al. (1991) suggest that in lettuce there is not much difference in economic result between dynamic temperature set-points and an optimized fixed set-point. The effect of spacing strategies on the optimal control policy for nitrate in lettuce is studied in Ioslovich and Seginer (2002)

Van Henten (2003) investigates the sensitivity of the optimal control solution to parameter uncertainties and model errors. Dynamic response times in the greenhouse climate do not seem to be limiting factors for economic optimal greenhouse climate control. Yet, the pseudo-static greenhouse assumption implies that the true costs of resource use are an approximation. As the greenhouse can only respond to changes in control inputs with some sluggishness, the actual patterns will be different from those assumed in the optimization. Ioslovich et al. (1995) show that the optimality of quasi steady state approximations degrades as the frequency of the external disturbance inputs increases. Some ideas of the sensitivity of the goal function to actual disturbances may also be obtained from Trigui, Barrington, and Gauthier (2001). A study by Tap et al. (1993) suggests that it is important to take the fast dynamics of the weather into account. Van Straten and Van Willigenburg (2008), who compare receding horizon control with PI control using set-points report simulated dynamic losses in a relatively low frequent case of already 5-10%.

Most studies have been restricted to temperature and CO_2 alone. However, rapid weather fluctuations as well as large deviations from assumed patterns will cause quite a different humidity regime in the greenhouse. Tap, Van Straten, and Van Willigenburg (1997), De Halleux and Gauthier (1998) and Van Henten (2003), have shown that in temperate climate zones, the humidity constraints have a considerable effect upon the ultimate economic result.

4.3 Integrated solutions and implementation

Within the class of integrated solutions a distinction can be made between knowledge based solutions without optimization (section 4.3.1), and solutions involving economically optimal control where both the fast and slow sub-problem are considered in conjunction (sections 4.3.2 and further). Emphasis is on implementable solutions.

4.3.1 Expert systems

The basic idea is that formalizing experience and expert knowledge could lead to improved – hence perhaps more economical – greenhouse operation. An early survey is provided by Martin-Clouaire, Schotman, and Tchamitchian (1996). A combination of a fuzzy knowledge based system (KBS), procedural control functions, and low level controllers is investigated in Sigrimis, Arvanitis, and Pasgianos (2000). Tchamitchian et al. (2006) discuss the expert system SERRISTE to generate daily climate settings for greenhouse grown tomatoes. In essence they handle control as a constraint satisfaction problem. The concept of crop vigor is introduced, based on visual inspection by the grower, in order to account for aspects of crop development that are not encapsulated by current crop models. A practical test against common practice revealed similar harvest rates, but with 5-20% lower energy consumption. Constraint satisfaction was also the basic approach of Schotman (2000), who was focusing on preventing blossom end rot in tomatoes.

A controller based on fuzzy rules is described by Lafont and Balmat (2002) and Kolokotsa et al. (2010). A good grower's behaviour can be mimicked by machine learning (Kurata and Eguchi (1990) or neural nets (Seginer (1997).

It should be noted that with expert systems there is no way to know how far these solutions are away from the optimum, except by simulation, but this requires a model, the absence of which is often the very motive to use an expert system.

4.3.2 Optimal control with direct application of computed controls

In general, direct application of the optimized controls is not robust against variations in external inputs. Pucheta et al. (2006) try to abate the robustness issue by frequent re-calculation of the slow problem by feeding back observed crop information in an application to tomato seedlings.

4.3.3 Hierarchical control with settings

A descriptive input-output discrete time model to approximate the behaviour of cucumber, Lagrange multipliers, periodical repetition of the optimization to cope with linearization errors, and temperature integral constraints have all been proposed in a early set of papers from the former GDR (Diezemann *et al*. 1986; Schmidt *et al*. 1987; Arnold 1988; Reinisch *et al*. 1989; Markert 1990). Yield improvements of 15% as compared to standard heuristic control are reported.

Tantau (1991, 1993), also proposes optimal control via set-points. Rodríguez et al. (2008) describe a hierarchical set-up using sequential programming to solve the seasonal optimization, and an hybrid MPC to cope with the switch in dynamics between heating and ventilation episodes. Van Henten et al. (2006) describe how a model for sweet pepper fruit formation (Buwalda et al 2006) is used to generate settings for a standard advanced climate control computer in a comparative experiment to try to counteract waves in fruit production that occur due to biological synchronization with negative effect on market price. Attempts are described to control sweet pepper in two counter-phase compartments, or to level out the on-set of fruits via optimal control of the climate.

4.3.4 Implementations of optimal control using meta information

Seginer and McClendon (1992) run dynamic optimizations for several years of historical weather data, and then train a neural network to arrive at temperature set-points depending upon the actual state and the actual weather, which can be used on-line, without the need for on-line optimizations; see also Seginer (1997). Similar ideas on greenhouse ventilation using experimental data are found in Seginer, Boulard, and Bailey (1994). In a study on controlling nitrate in lettuce, De Graaf (2006) translates the off-line optimal control solutions in a set of rules to be followed on-line.

4.3.5 Integrated optimal control with on-line optimization

Pohlheim and Heissner (1996) and Pohlheim and Heissner (1997) use a genetic algorithm to find optimal piece-wise constant controls for heating, ventilation and CO_2-dosage using accumulated photosynthesis as crop value. Due to computation time limitations, new solutions are generated every two hours. A receding horizon optimal control of the form of (15) with a control interval of 1 minute and a horizon up to an hour was implemented in a real application for a tomato production during the reproductive stage, as described in Tap, Van Willigenburg, and Van Straten (1996), Tap, Van Straten, and Van Willigenburg (1997), Tap (2000). An experimental comparison of an optimally controlled greenhouse with a traditionally controlled greenhouse was made, showing that yield and quality are comparable. Computation of the economic benefit by simulation shows that 10-15% savings are easily obtained. Van Ooteghem (2007) applies the receding horizon optimal control methodology to a design of a novel solar greenhouse with long term heat storage in an aquifer in conjunction with a heat pump, showing similar benefits of the optimal control.

5. OPEN PROBLEMS AND FURTHER RESEARCH

Because of space limitations, a full account on open problems and need for further research cannot be given here, and we only present a brief summary. Details are given in Van Straten *et al*. (2010). References to these issues can also be found there.

Sensors

Control in its current form is essentially open loop with respect to the crop. Therefore *crop sensors*, and more notably methodology to interpret individual plant sensor results on the canopy level, are high on the wish list. This may be achieved with model based sensor methodology, also called *soft sensors*, which is, in fact, a form of state estimation. *Spatial heterogeneity* is another issue, for which wireless sensor networks may be helpful. *Sensor fusion* might become an issue.

Models

In the greenhouse, still improvements are needed to predict *humidity*, which appears to be hard due to time varying evapo-transpiration and the effects of condensation and back radiation. The proper modelling of *condensation* is important in particular for water recovery in hot climates. More work on developing *spatial models* that are suitable for control (i.e. beyond CFD) is desired. As to the crop, *state space* representations for current agronomic models are needed. Wider applicability of optimal control can be reached by generic methods for *partitioning* of assimilates, and for *crop development,* and *quality*. *Stress* and *vulnerability* models may contribute to justify current operational ranges, or to expand them. Regarding modelling methodology, abating lack of detail by *time variable parameters* require *on-line estimation methods*. The selection of parameters for *calibration* is not trivial. *Validation* of models requires consideration of the natural variability and *uncertainty* in biological systems. In existing greenhouses, improved methods for data-based *identification* with recursive methods or dynamical artificial neural nets are also of interest. More work on *model reduction* to speed-up computations and to improve transparency is envisaged.

Goal function

More insight is needed into the *economic variability* of product and commodity prices, in the light of contracting and energy policies. Thus far, incorporation of *risk* has hardly have had attention. The stochastic nature of the weather makes that *the goal function value is a stochastic variable*, with consequences for control that still need to be investigated. Another issue is how to provide handles to the user, e.g. *co-states*, in a user interpretable way.

Optimization and control methodology

The avoidance of *local minima* needs more attention. Genetic algorithms have been applied to achieve this, but these methods are usually not very efficient. *Computational speed* although sufficient for on line control with control interval of, say 10 minutes, is still an issue for year-round simulation. Hardware solutions such as Field Programmable Gate Arrays (FPGA) might be considered here as well. In *receding horizon control* there are still debates on the optimal selection of prediction horizon and control interval. *Control methods for spatial heterogeneous systems* must be explored. *User transparency* and an *explanatory facility* may contribute to faster dissemination. *Near optimal* control can help to find simplified solution, that can be implemented more easily. It is also worth to investigate the potential of obtaining a closed control law with NCO tracking methods (necessary conditions of optimality (8)). Adoption of optimal control would be speeded up if the systems had *self-learning* and *self-optimizing* capabilities.

6. CONCLUSIONS AND PERSPECTIVES

The framework presented has helped us to present an overview of the current state of affairs in greenhouse cultivation control. In view of the many advantages of protected cultivation over open air cultivation it can be expected that the greenhouse industry will show substantial growth, especially in upcoming economies. It is likely that under pressure of the growing awareness on sustainability, there will be increasing focus on energy and water savings, with nearly complete independence of external sources as the ultimate aim. Not only will this make greenhouse systems more and more complex, but it will also constitute a challenge to designers and vendors of control systems. We expect that there will be a larger scope for optimal control methods, as it would make little sense to spoil splendid innovative designs by poorly conceived control. Despite the challenging list of issues that need further investigation, it is our strong opinion that the current state of knowledge is already enough to start using economic optimal control in practice.

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