ON-LINE OPTIMAL CONTROL OF GREENHOUSE CROP CULTIVATION

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Abstract

Thus far, optimal control has primarily been investigated for seasonal crop growth optimization. On-line aspects have received much less attention. The decomposition between long term strategies and on-line control, however, is not trivial. Appreciable losses occur when set-points generated by seasonal optimization using nominal weather and the static physics assumption are put to the fully dynamic system. It is argued that the main product of seasonal optimization are not the state trajectories of the fast variables, but rather the state trajectories, and the co-state trajectories of the slow variables. The co-states represent marginal values of the slow variables. The actual on-line control requires the solution of a new dynamic optimization problem over a far shorter horizon, with a modified goal function incorporating the marginal value of all slow crop variables (not just the harvested parts). Feed-back and feed-forward to account for modelling errors and weather deviations can be accounted for by receding horizon optimal control, using the actual measured weather and fast states.

An feasible economically optimal greenhouse crop control and operation system thus may consist of three major elements: (i) specification of constraints that pertain to unmodelled management aspects, possibly supplied by expert systems or other AI decision support, (ii) a solution to the seasonal slow crop response optimization using known long term nominal weather, and (iii) a receding horizon optimal control to generate short term controls responding to the actual weather and state, using crop state and co-state information from the slow optimization.

1. Introduction

Greenhouses are used as protected environments to grow crops that otherwise could not be grown economically. Yet, present greenhouses are not fully closed systems over which free control is possible. Most notably, solar radiation is a necessary production factor, which by its very nature constitutes a disturbance that should not be rejected by the control system, but rather exploited. In addition, the usual design with ventilators to the open air causes control difficulties, because this control variable has to be used for both heat and humidity control, while it also affects the carbon dioxide balance as well.

Moreover, the presence of a changing crop has a significant impact on the dynamics. All this is further complicated by considerable uncertainty as to which climate is best for high crop yields and good crop quality.

Presently, greenhouse climate computers are widely used in the horticultural industry. Originally, single loop controllers were installed to automate e.g. temperature and humidity control. Because these loops have to operate at least partly on the same actuators, decision rules were needed to decide on controller priority or balancing. Gradually, also feed-forward compensation was introduced to account for high or low

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radiation, and other environmental factors. In addition, climate 'blue prints' were generated from experience and from cultivation experiments, which defined state trajectories or trajectory ranges. Since computers are very suitable for time sequencing tasks, and also can easily handle decision rules, climate computers penetrated very quickly into the market. Responding to demands by growers, more and more options were build in, and presently growers have access to hundreds of settings.

There are a number of reasons why it is desirable to revisit operational greenhouse control:

- The large number of settings constitutes a significant difficulty for growers. Practice has shown that errors are made quite often. Some settings require a deep insight in the details of the controllers used, and have little to do with the grower's ultimate aim.
- The various, sometimes counteracting controllers set doubts to the economy of operation. Heating and venting at the same time are just one example of energy losses that could possibly be largely avoided.
- Finally, the scientific basis of 'blue prints' is often weak, as illustrated by the large differences in yield and quality among growers.

There are a number of reasons that make it possible to revisit operational greenhouse control:

- The gradual dissemination of models for greenhouse physics, for photosynthesis and transpiration, and for crop growth and development stage.

- The progress made in fundamental control theory.

Dynamic optimal control provides a very promising framework to tackle the problems outlined above. The method is based on appropriate models of the greenhouse and crop behaviour, and the formulation of an explicit economic goal function. Optimal control frees the grower from incomprehensible technical control settings, automatically takes care of the interactions, and, if the models are correct, assures the best economic control possible. The purpose of this paper is to give an outline of optimal control as a unifying framework to greenhouse crop control, and to discuss the amendments needed to make the approach feasible in practice.

2. Open loop optimal control

2.1. Fundamentals

Let the system be described by a set of non-linear ordinary differential equations:

$$\dot{x} = f(x, u, d) \tag{1}$$

where x(t) is a vector of state variables (e.g. temperature, CO_2, humidity, fruit dry weight, stem dry weight, etc.), u(t) is a vector of control inputs (e.g. heating flux, window opening, CO_2 dosage), and d(t) is a vector of known external influences (e.g. solar radiation, outside temperature, wind speed, etc.).

The basic idea of optimal control is to generate a sequence of controls u*(t) such that the associated path x*(t) given by equation (1) is optimal in some sense. This problem can be expressed as follows. Given the model of Eqn. (1) with proper initial conditions, together with a goal function

$$J = \Phi(x(t_f)) + \int_{t_o}^{t_f} L(x,u,d)\,dt \tag{2}$$

where b is a value associated to the states at the final time t_f, L are the instantaneous benefits minus costs associated to the state and control trajectories, and requirements imposed on the final state

$$\psi(x(t_f)) = 0 \tag{3}$$

find the time evolution u*(t) of the controls such that Eqn. (2) is maximized, while satisfying the terminal conditions Eqn. (3) and the state equations (1). A well known method to solve this problem is by the Hamiltonian approach. First, the Hamiltonian is formed

$$H = L + \lambda^T f \tag{4}$$

The column vector $\lambda(t)$ represents the so called adjoint variables, or co-states, and are introduced to incorporate the system equation as a constraint in the optimization. There are as many co-states as state variables. The co-states are used as intermediate auxiliary variables, which allows the minimization of J, such that the optimal state and control trajectories, x*(t) and u*(t), also obey the systems dynamics equation (1). Note that the Hamiltonian is a scalar. Necessary conditions can be derived (Lewis, 1986), and several numerical solution techniques have been proposed (e.g. Bryson and Ho, 1975). In greenhouse control it is attractive to express the goal function in money units directly. In that case, there is a direct interpretation of the co-state variables. They represent the marginal value per additional unit of the variable, i.e. in the optimum the benefits of increasing the variable are just balanced by the additional costs.

2.2. Requirements and limitations

Thus, the necessary ingredients of optimal control are:
- a model of the systems dynamics
- trajectories of the uncontrollable external inputs
- a goal function constraint conditions (if any)
- a solution algorithm.

Note that the optimal solution is essentially an open loop solution: in its basic form the control sequence is computed in advance. Note also that in its basic form the controller has no set points. The desired trajectories are computed, as well as the control inputs needed to achieve them.

The optimal control scheme as outlined above cannot be directly applied to the actual greenhouse because:
- the stiff properties of the greenhouse-crop system causes computational difficulties
- the external disturbances are not known
- the models are incomplete and subject to errors.

3. Properties of the greenhouse crop system

The greenhouse system can be conveniently represented by the following set of differential equations:

$$\begin{aligned} \dot{x} &= f(x,z,u,d) \\ \dot{z} &= g(x,z,u,d) \end{aligned} \tag{5}$$

where x represent the 'slow' state variables, related to the crop, e.g. dry weight, leaf area, roots, shoots, fruits, etc., and z the 'fast' state variables, related to the greenhouse physics, e.g. temperature, humidity and CO_2. The symbol u is a vector of control variables, e.g. the heat supply, ventilation rate, CO_2-dosage, or - with some complications not discussed here - the heating valve position, the window openings and the CO_2-valve opening, as well as the operation of assimilation lighting, screens and moisturizers. The external disturbances, e.g. solar radiation, outside temperature and humidity, etc. are represented by d. First order approximate time constants for the slow variables are in the order of days or weeks, while for the fast variables they are in the order of minutes or hours. The 'fast' states form the environment for the crop, but the system is highly interactive because the crop has a considerable influence on the climate variables, due to photosynthesis and transpiration, which are practically instantaneous.

The greenhouse is subject to external disturbances. While in usual control problems disturbance rejection is one of the major goals, this is only partly the goal in greenhouse crop control. In particular, solar radiation is a production factor, and must be exploited, while the outside air CO_2 concentration can sometimes be used as source. The difficulty is, of course, that the external inputs are not fully known in advance. Generally long term averaged patterns are, however, available. That is, it is possible to write

$$d(t) = \bar{d}(t) + \tilde{d}(t) \tag{6}$$

where the over bar denotes the average at that particular time over years (this employs repetition of the annual cycle), which is a known function of time, and the tilde denotes the variation, which is not known, nor necessarily small. On the other hand, in greenhouse control the major external inputs can all be measured. It is also important to note that the known component of the signal has a spectrum in lower frequencies, typically 1 d^{-1} or slower, while the unknown component is faster - in the case of solar radiation, for instance, it can be in the order of 0.2 min^{-1}

4. Heuristic decomposition

The different time scales suggest a decomposition of the optimization in a slow and a fast sub-system (e.g. Tantau, 1993). Several researchers (Gal et al., 1984, Seginer et al., 1986, Van Henten and Bontsema, 1991, Chalabi, 1992, Seginer and Sher, 1993) have studied the optimal solution of the slow system or parts thereof by considering

$$\begin{aligned} \dot{\bar{x}} &= f(\bar{x},\bar{z},\bar{u},\bar{d}) \\ 0 &= g(\bar{x},\bar{z},\bar{u},\bar{d}) \end{aligned} \tag{7}$$

Here, the over bars refer to the slow variation, under nominal weather conditions. The fast states $\bar{z}$ are computed by assuming that the greenhouse system reaches steady state immediately, as compared to the time scale of the slow variables. Due to the variation in $\bar{d}$ and $\bar{x}$, $\bar{z}$ is a function of time.

The result of this seasonal optimization, using the Hamiltonian approach, is a sequence of optimal controls $\bar{u}^*(t)$, optimal slow states $\bar{x}^*(t)$ and associated adjoint variables (co-states) $\bar{\lambda}^*(t)$, and a sequence of fast quasi-steady state states $\bar{z}^*(t)$. One may consider this optimization as equivalent to the optimization of the slow system using the fast states as inputs. The quasi-steady state equation is needed to compute the associated costs via the controls u.

Although seasonal optimization of this kind is very useful to gain insight in the optimization process, and the findings may be used to derive rules how to relate climate set-points to outside conditions, the direct application to on-line control is not without difficulties. First, it is immediately clear that the slow control sequence is not very useful for actual control, because of the lack of feed-back. That is, due to the neglected greenhouse dynamics and weather deviations, different control actions would soon be required. It is less immediately clear, however, that also the use of the calculated fast state responses as set-points to low level controllers may lead to loss of performance. In simulations for a lettuce cultivation using the a posteriori known measured weather d (rather than d) Van Henten (1994) has shown a considerable loss in performance if the fast states were offered to the dynamic system equipped with a simple controller. The reason probably is that the costs assumed during the quasi-steady state assumption are quite different in the dynamic situation. On top of this, maintaining the precalculated set-points in the presence of deviations of the actual weather from the nominal pattern will also lead to losses. This is easy to see if one considers CO_2. Under low light conditions it would not be cost effective to try to maintain a set-point calculated under averaged light conditions. Conversely, on a bright day, no benefit is made of the higher solar radiation. Apart from this, the operation of the windows would almost certainly be different than assumed in the optimal conditions, thus spoiling the optimization completely. So, a linear compensator as sometimes used in e.g. robotics, is not suitable for greenhouse crop control.

5. Decomposition revisited

Van Henten and Bontsema (1992) and Van Henten (1994) have studied the two-time scale decomposition using singular perturbation theory. The major finding of his study is two-fold. First, the control of the fast response can be formulated again as an optimal control problem, in which the slow state variables $\bar{x}$ act as known trajectories. Second, the goal function for this sub-problem does not only contain the integrated costs, but must also account for the marginal value of a deviation of the slow crop variables from their slow trajectory. This information is available from the seasonal optimization. The goal function for the short term problem thus is different from the overall goal function, because in the short term problem not just the harvestable parts but every slow component of the plant has a marginal value. This prevents the short term optimization from unduly favouring fruit growth over leaf growth.

The results clearly show that the most important product of the nominal weather/static greenhouse seasonal optimization of Eqn. (6) is the co-state information, and the state patterns for the slow variables, not the fast state trajectories $\bar{z}$. The optimal states z* follow from the fast sub-problem.

In the fast sub-problem, the actual weather conditions, and the weather conditions in the near future have a definite impact. Application of open loop solutions would soon lead to serious deviations. In order to properly cope with the actual weather, the optimal control problem can be cast in the frame of receding horizon optimal control (RHOC), as proposed by Tap et al. (1993). In RHOC the problem is solved over a horizon in the order of the fast time scale. Tap (1994) has shown that the application of the 'lazy men's prediction' of the weather, i.e. the weather will remain the same as measured now, leads to good results. Only control variables calculated for the coming control interval (usually some minutes) are applied to the greenhouse, and next the optimization is repeated, shifting the end time one step up. An important feature is that the calculation starts from the last observations, rather than the model values, thus making the actual outcome much less vulnerable to modelling errors. Note that optimal control automatically implies feed-forward compensation, because the model is used to calculate the effects of measured disturbances.

Other options to introduce feed-back are conceivable. For example, one could replace the greenhouse physics by greenhouse plus low level controller of any kind (for instance Young et al., 1993), and calculate the set-points for the slave controller on the basis of the fast optimization sub-problem. Note that it is essential in this case to consider the dynamics of greenhouse plus local controllers jointly. The advantage of this approach may be a larger flexibility and reliability in practice.

The slow sub-problem may also suffer from some deterioration in response to longer lasting deviations from the nominal weather, and due to modelling errors. Correction of this would require measurement of the status of the plant, which is not regular practice at present. State updates need not be done very frequently, though, so that off line measurements from samples are conceivable. Of course, both the slow and the fast problem would profit from instantaneous plant measurements like photosynthesis, water evaporation, leaf area etc, e.g. by the speaking plant concept (Hashimoto, 1993)

6. The availability of models

Optimal control heavily relies upon the availability of models.

In general, the physical part constitutes little difficulty. Some crucial parameters like heat capacities of plant and soil, and the parameters of the ventilation flux may need to be estimated from time series data. In cultivations with humidity surplus, a humidity balance is necessary. Otherwise, optimal temperature and CO_2 control would calculate window openings that cannot be maintained because of moisture problems, and the calculated control would be useless. Experience with optimization for lettuce and tomatoes has shown that the humidity constraints have a pronounced effect upon the results. A particular problem is the condensation on the glass cover, which can be a substantial contribution to the moisture (and heat) balance. Approximate solutions avoiding the introduction of the cover temperature as an additional state variable have been proposed. Also, plant transpiration has to be incorporated (see below).

Since the plant is an essential part of the greenhouse, models for the fast plant responses are indispensable. Reasonably reliable models are available to describe photosynthesis as function of light, CO_2 and leaf area. Photosynthesis seems not to be very plant specific. Transpiration is more difficult to model. One difficulty is the need of the leaf temperature as an additional state variable, which can be eliminated only at the expense of approximation errors.

The assimilated material will be used in the plant for growth and maintenance energy. A crude picture is that non-structural dry weight formed by photosynthesis is converted into different kind of structural dry weights, with some simultaneous loss due to respiration. Temperature seems to be the major factor influencing both growth and maintenance. Models for growth along the line shown above are rather generic (e.g. Seginer et al., 1993, Van Henten, 1994)

The difficulty in modelling crops, particularly non-vegetative crops, is to find out how the biomass is distributed over the roots, stem, leafs and fruits. Only a first start has been made in modelling crops like tomatoes and cucumber, and very little is available for flowers. The significance of the partitioning response to optimal control is as follows. If the goal function would only favour the production of biomass, without giving due account to the distribution, the optimal control invariably leads to low night temperatures. The reason is that during night there is no photosynthesis, and since respiration is lowest at low temperatures, as are the heating costs, the optimal control scheme will push the temperature down (e.g. Tchamitchian et al. 1993). Yet, cultivation experience seems to indicate that this is unrealistic for most crops. On the other hand, if the distribution is taken into account, such behaviour does not occur, because the long term optimization will need to make sure that the plant growth is well balanced so as to maintain its long term production capacity. For instance, short term profit by favouring fruits would be punished later when the lack of leafs hampers further plant development.

So, from an (long term) optimal control point of view, proper description of the distribution is essential. Yet, there is considerable debate whether this is already possible at the current state of knowledge. Moreover, this knowledge will be quite plant specific, making the control scheme less flexible and generic. So, one school of thought is to refrain from modelling plant partitions at this stage. In this view one should try to define temperature boundaries, or preferably an acceptable range for the temperature integral, on the basis of experience and cultivation experiments. Then, optimal control is used only to assure an energy effective distribution of the heating over a day, and to manipulate CO_2 dosage for optimal photosynthesis. In this approach the optimization boils down to a 24 hour optimal control that should satisfy present temperature (integral) conditions (Gutman et al., 1993).

The other school advocates to incorporate in models whatever quantitative knowledge is available, despite its limitations. Reasonable descriptions for the distribution for certain crops, like tomato, already exist. Models developed by horticulturists (e.g. De Koning, 1994) usually are too detailed but can be transformed into models suitable for control. Thus, some of the qualitative knowledge contained in integral or state constraints is replaced by quantitative models.

Yet, some aspects that are nevertheless of great interest to the grower, like flowering, crop quality and sensitivity to diseases remain untouched. Consequently, even in the model oriented approach the specification of desirable boundaries on humidity and temperature, and possibly integral constraints can not be avoided. It is worth while to note that this argument can also be turned upside down: the main vehicle to allow the grower to interact with the control system in order to achieve goals that cannot be expressed in models is via constraints. In other words, the constraint specification is still an important tool for the grower to manipulate his crop.

7. Outline of feasible solution

The analysis above now enables us to refine the earlier ideas (Gal et al., 1984, Challa and Van Straten, 1993) and to draw an outline of a feasible solution to economically optimal on-line greenhouse operation.

First, the intangibles of the crop development are translated into constraint conditions. This is basically the responsibility of the grower, and allows him to use his skill and experience. During the cultivation he observes the state of the crop, and has the opportunity to adjust the constraints. Here, of course, there is also great potential for user support systems based on methods from artificial intelligence (Martin-Clouaire et al., 1993, 1994), like expert systems, constraint satisfaction (Martin-Clouaire, 1993) and qualitative-quantitative models like fuzzy models, which may help to separate myths from real phenomena (see also Hashimoto, 1993).

Second, using models of crop growth and development, and the slow, known component of the external disturbances, a long term optimization is performed. With generative crops like tomatoes there is perhaps an option to limit the calculation to a repetitive daily cycle during the stationary fruit production phase. The major outcome of this optimization is not so much the control pattern, nor the state pattern of the fast variables, but rather the state pattern of the slow variables, as well as the co-states. This computation is performed off-line.

Next, the fast control problem can be solved on line, using receding horizon control over a limited horizon. The marginal value of the slow states originating from the slow optimization are used, as well as the actual weather and a short term outlook.

8. Discussion and conclusion

Optimal control is attractive because of its optimality. The research achievement briefly outlined above hold promise that a number of practical problems that must be solved before application in practice is possible are, indeed, solvable. Preliminary simulation results have shown that considerable energy savings (certainly between 10 and 20%) can be expected, while maintaining or even improving crop yield. Now the time has come to test and adjust these concepts in practice (Tap et al., 1994).

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