

MODELING AND CONTROL FOR CLOSED ENVIRONMENT PLANT PRODUCTION SYSTEMS

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Abstract

A computer program was developed to study multiple crop production and control in controlled environment plant production systems. The program simulates crop growth and development under nominal and off-nominal environments. Time-series crop models for wheat (*Triticum aestivum*), soybean (*Glycine max*), and white potato (*Solanum tuberosum*) are integrated with a model-based predictive controller. The controller evaluates and compensates for effects of environmental disturbances on crop production scheduling. The crop models consist of a set of nonlinear polynomial equations, six for each crop, developed using multivariate polynomial regression (MPR). Simulated data from DSSAT crop models, previously modified for crop production in controlled environments with hydroponics under elevated atmospheric carbon dioxide concentration, were used for the MPR fitting. The model-based predictive controller adjusts light intensity, air temperature, and carbon dioxide concentration set points in response to environmental perturbations. Control signals are determined from minimization of a cost function, which is based on the weighted control effort and squared-error between the system response and desired reference signal.

1. INTRODUCTION

Methodologies for utilizing information from plant growth and development studies within controlled environments for decision support purposes, such as planning, design, assemblage, and operation, would be useful for controlled environment plant production systems. The ideal situation would be the construction of a computer platform to represent all mathematical, logical, and heuristic representations of related plant growth and development information (Fleisher *et al.*, 2000a). Although such a device is not currently available, it is possible to draw useful conclusions from simpler computational tools.

For example, many modern greenhouse control approaches employ mathematical models of the greenhouse environment and the crops to prescribe daily environmental set points for the greenhouse. These strategies produce greenhouse management tools and control systems that dynamically determine optimal setpoints based on some objective function (see, for example Aaslyng *et al.*, 1999; Klaring *et al.*, 1999; Seginer *et al.*, 1999). There has also been

interest in incorporating feedback measurements on crop growth into the controller design to adjust environmental setpoints on a real-time basis. For example, Chun *et al.* (1996) developed a dynamic controller using light intensity to control lettuce net photosynthesis based on real-time measurements of canopy gas exchange. Fleisher *et al.* (2001) explored the potential use of a pointwise-optimal controller to adjust daily light intensity levels to control wheat growth rate provided with feedback on plant growth at the previous time increment.

This project evaluates the use of non-linear plant growth models to simulate plant response (daily growth and development) to daily environmental inputs. A computerized decision support tool was developed to provide user access to these models. The tool allows study of different multiple crop production scenarios and can estimate the effects of uncontrolled environmental disturbances on crop production scheduling. A prototype model-based predictive controller (MBPC) algorithm was developed for process control of total and yield dry biomass. The MBPC uses the non-linear crop models to determine optimum daily environmental set points (photosynthetic photon flux (PPF), average daily air temperature (T), and atmospheric carbon dioxide concentration (CO₂)) for a biomass production facility (e.g. growth chamber) based on plant growth model forecasts.

2. MATERIALS AND METHODS

2.1 Crop Models

Detailed, explanatory crop models for controlled environment plant production were reduced into a mathematical form more tractable for control application and system studies. Three DSSAT crop field models (Tsuji *et al.*, 1994) had been previously modified to simulate growth and development within controlled environments with hydroponics production systems. The wheat model, based on the model CERES, was initially modified by Tubiello (1995) and further modified by Cavazzoni (unpublished). The soybean model, based on the model CROPGRO, was modified by Cavazzoni (1997). The white potato model, SUBSTOR, was subsequently modified by Fleisher *et al.* (2000b).

Over forty-five simulations were conducted with each modified model to generate output data for daily total plant dry mass and yield dry mass values as a function of different combinations of environmental inputs (PPF, T, CO₂) held constant throughout the production cycle. All other inputs were assumed to be at their nominal values. Multivariate polynomial regression (MPR) (Vaccari *et al.*, 1999) was used to develop a set of six non-linear regression equations using this data for each crop (Figure 1). MPR is similar to multilinear regression in that a single dependent variable is mathematically expressed as a function of several independent variables. However, MPR can also include non-linear and interactive combinations of the independent variables in the mathematical expression.

The dependent variables for three of the six MPR equations are the relative growth rates of (a) total dry mass prior to formation of yield bearing organs, (b) total dry mass after the formation of yield bearing organs, and (c) yield dry mass. The independent variables used in each equation include the average PPF, T, and CO₂ values (averaged from planting date up to the current time increment t), and the total or yield dry mass at $t-1$. The general expression for these three equations is:

$$R_v(t) = \frac{1}{V(t)} \frac{dV(t)}{dt} \approx \frac{(V(t) - V(t - \Delta t))}{V(t)\Delta t} = f(V(t-1), PPF, T, CO_2) \quad (1)$$

where:

$R_v(t)$ – relative growth rate of V at time t discretized using a forward-difference approximation

$V(t)$ – total biomass or yield dry mass at time t

Δt – time increment (= 1 day)

Two additional MPR equations estimate important developmental dates: (a) date of observable yield biomass formation (TI) and (b) maturity date (TM). The sixth and final MPR equation estimates the yield mass at TI . The net result is a set of six non-linear equations that can be used to predict the daily growth rate of vegetative and yield organs and important developmental stages for each crop. The equations can be used to predict daily plant responses to changes in environmental conditions during the growth cycle.

2.2 Model-Based Predictive Control

In model-based predictive control (MBPC) (Figure 2), an observer, or mathematical model, uses the control inputs \mathbf{u} , and measurements of the system \mathbf{y} , to obtain an estimate of the system state $\hat{\mathbf{x}}$. The optimizer is a routine that attempts to compute new control inputs that minimize differences between desired reference signals and the state estimates. In this application, the processes to be controlled are the yield and total biomass growth rate of the crop; thus, $\mathbf{x}(t)$ represents the yield and total biomass dry mass at the given time increment t . The $\mathbf{u}(t)$ are the values for PPF, T, and CO_2 specified at time t . MPR crop models are used to derive $\hat{\mathbf{x}}(t)$ from values for $\mathbf{y}(t-1)$, $\mathbf{u}(t-1)$, and $\mathbf{x}(t-1)$. For purposes of testing the MBPC algorithm through simulation, it was assumed that $\hat{\mathbf{x}}(t)$ was identical to $\mathbf{x}(t)$ and thus, the values predicted by the MPR crop models were assumed to be perfectly correlated with actual plant growth.

At the beginning of each time increment, the MPR models are also used in the optimizer routine to predict plant behavior from time t to the maturity date, TM in response to the control input values. These values are held constant for each day beyond $t+1$ during this process. That is to say that $\mathbf{u}(t+1) \dots \mathbf{u}(TM) = \mathbf{u}(t)$ within the optimizer routine. The optimizer attempts to compute a optimum set of environmental inputs, $\mathbf{u}(t)$, to be applied for the current day that forces the plant growth to follow a reference production schedule. This is accomplished through minimization of the cost function $J(e, \mathbf{u})$ in equation 2. The optimizer uses the Nelder-Mead method (Press *et al.*, 1988) to minimize $J(e, \mathbf{u})$ with respect to $\mathbf{u}(t)$.

In equation 2, reference signals $\mathbf{r}(t+j)$ are determined by the MPR time-series predictions of the crop assuming that the nominal environmental conditions throughout the production cycle were achieved each day. $J(e, \mathbf{u})$ is thus composed of the squared-error between the desired growth rate and the model-predicted one using the observed environmental inputs, plus a weight on the amount of control effort required to minimize this difference. This control weight, λ , was determined via trial and error for each of the three control inputs.

$$\mathbf{J}(\mathbf{e}, \mathbf{u}) = \sum_{j=1}^{TM} \left(\mathbf{r}(t+j) - \hat{\mathbf{y}}(t+j) \right)^2 + \lambda \Delta \mathbf{u}(t)^2 \quad (2)$$

where:

- $\mathbf{r}(t+j)$ – desired dry mass at time step $t+j$
- $\mathbf{y}(t+j)$ – model predicted dry mass at time $t+j$
- $\Delta \mathbf{u}(t)$ – change in control inputs from time $t+1$ to t
- TM – crop maturity date
- λ – control weighting constant

2.3 Software Platform

Microsoft's Visual Basic™ v6.0 programming language was utilized to construct a decision support system with user access to crop models and the MBPC algorithm. The program provides the user with the ability to conduct simulations with:

- (1) Multiple crop scenarios. The user can select from one to three crops to be included in the simulated production scheme. Environmental inputs for PPF, T, and CO₂, can be manually input for study or the program can be instructed to automatically search for input values that will potentially optimize yield or total biomass for all crops in the scheme.
- (2) Sensitivity analysis. The user can evaluate effects of manipulating environmental inputs during the production cycle on plant scheduling.
- (3) Model-based predictive control. Environmental inputs can be input into the software program each day. The MBPC algorithm conducts the following steps:
 - i. Predicts the growth rates and resulting plant dry weights ($\hat{\mathbf{x}}(t)$) using the appropriate MPR crop models based on the environmental inputs,
 - ii. Compares $\hat{\mathbf{x}}(t)$ with the desired dry weight values $\mathbf{r}(t)$,
 - iii. Computes and minimizes $\mathbf{J}(e, u)$ with respect to $\mathbf{u}(t)$ assuming that future values for environmental inputs will be at the desired level if there is a significant difference in step ii.
 - iv. Replace old set of inputs with new $\mathbf{u}(t)$.

3. RESULTS

Simulations with the software program were conducted for evaluation purposes. Table 1 shows the environmental conditions that the program found as optimal for achieving maximum yield for different crop mixes and demonstrates item (1) in the previous section. Although only the final yield at maturity is provided in the table, the program tabulates yield and vegetative mass for each day over the growth cycle (not shown).

The MBPC algorithm was evaluated, through model simulations, for the ability to compensate for a hypothetical 20 day –30% reduction in PPF with a white potato production scenario (Figure 3). In other words, the PPF level is reduced from the nominal value of 800 $\mu\text{mol m}^{-2} \text{s}^{-1}$ to 560 for twenty days, after which it is restored to 800. Plant growth is shown

as a time-history plot of yield mass (g m^{-2}) for three simulated cases: nominal growth (where PPF is held at 800 throughout the growth cycle), actual growth (where PPF is reduced by 20% for the 20 day period and then returned to the nominal level after the disturbance), and control growth (where the MBPC algorithm is applied). At maturity date (day 137), the actual case shows a -11% decrease in yield dry mass. This is the result when no control is applied. At maturity date with the control case, there is a +1% deviation from the reference nominal yield mass. The graphs on the right of the figure show the time-history of the control inputs for PPF, CO_2 , and T for the control growth case.

4. DISCUSSION

The values in Table 1 for PPF and CO_2 are at the highest levels permitted by the program. Temperature varies depending on selected crop mix (Table 1). This result is not surprising as increases in light energy and ambient carbon dioxide concentration will have the most direct affect on promoting growth rate. Increases in temperature will generally promote yield for soybean and reduce it for potato and wheat. Thus, temperature is most critical for permitting scheduling of multiple crops under shared environmental zones. However, in general, reducing temperature tends to increase the length of the production cycle (data not shown) so a compromise needs to be worked out between maximizing yield and the time between planting and harvesting.

In Figure 2, the curve for actual growth shows the simulated PPF disturbance created a significant deviation from the desired, nominal growth curve. The MBPC algorithm performed well in compensating for the disturbance as shown by the control growth curve. The control inputs specified by the algorithm are shown versus time on the right hand side of the figure. A similar ability to compensate for disturbances in PPF, T, and CO_2 (not shown) was obtained with other perturbation simulations with each of the three crops. In all cases, using the control action was better than not compensating for the disturbance. However, in each case, some undesirable oscillations appear in the T and CO_2 inputs. The results suggest that with further refinement the software program and MBPC algorithm could be a viable method for providing real-time decision support for controlled environment plant production operations.

While the MPR equations do not offer a mechanistic basis for predicting the plant responses to environmental changes or for estimating the physiological effects on the plants, the correlations between growth rate and environmental input variables are statistically significant (r^2 greater than 0.85 in all equations). The non-linear regression equations should be accurate within the range of environmental inputs for which they were originally developed. However, the equations were developed from a simulated dataset. Future work includes validation and improvement of the MPR models based on actual experimental data. The models are also restricted in terms of other independent variables such as humidity and photoperiod. These factors will be important to include in the models.

While the model-based predictive controller provides reasonable results as simulated, it should be validated in a real-world setting. Instead of using the MPR models to predict the state of the crop, a significant research step will be to estimate the state based on real-time measurements of crop growth. Such measurements would realign the controller at each time

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step by providing feedback of the crop. Additional tuning of the cost function $J(e,u)$, such as adjustments to the control weight values can help optimize the control response.

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Table 1. Simulated optimal environment inputs to maximize combined yield for given crop mix.

crop mix	PPF ¹ [$\mu\text{mol m}^{-2} \text{s}^{-1}$]	T [$^{\circ}\text{C}$]	CO ₂ ² [ppm]	Yield (g m^{-2})	Harvest Index ³
wheat	1700	14	1600	2783	0.40
soybean	1200	30	1600	779	0.58
white potato	1200	14	1600	3716	0.68
wheat / soybean	/ 1200	26	1600	1085 / 722	0.34 / 0.55
wheat / potato	1200	14	1600	2273 / 3716	0.40 / 0.68
soybean / potato	/ 1200	24.5	1600	700 / 3716	0.53 / 0.74
all three crops	1200	20	1600	1669 / 626 / 3249	0.37 / 0.38 / 0.63

¹PPF range was restricted to 1700 for wheat models, and 1200 to soybean and white potato

²Maximum CO₂ concentration was restricted at 1600 ppm

³Harvest index computed as yield / total biomass where total biomass includes leaves, stems, roots, yield organs and senesced leaves

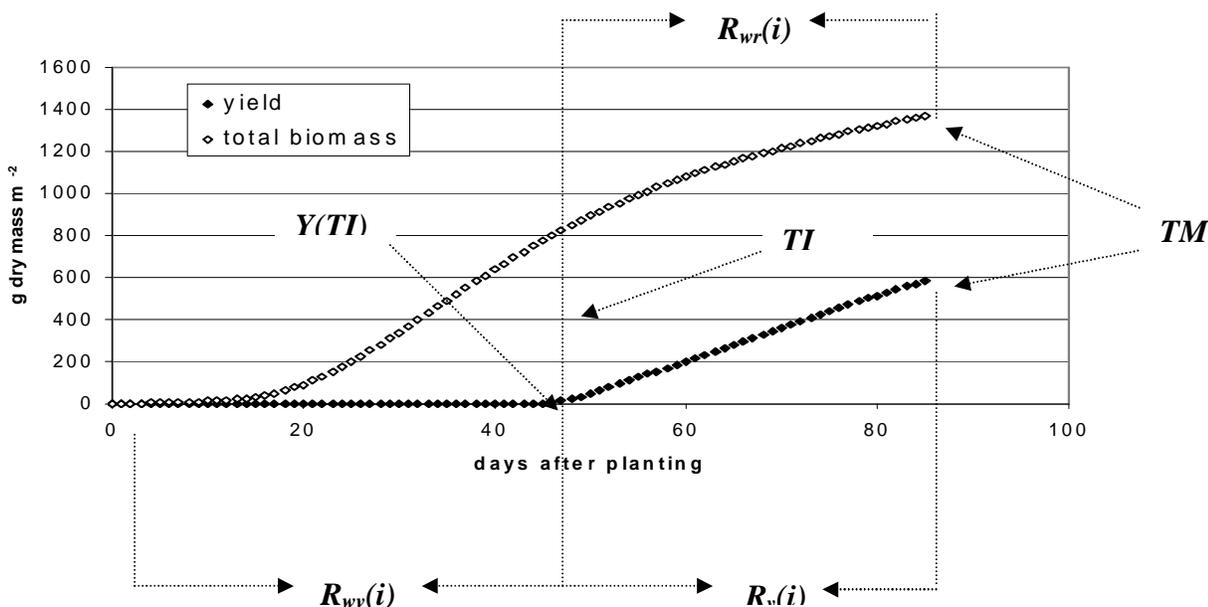


Figure 1: Illustration of MPR model application. Three MPR equations are used to predict relative growth rate of yield and total dry mass. $R_{vv}(i)$ predicts vegetative growth of the plant prior to formation of yield organs. $R_y(i)$ predicts yield growth rate after the appearance of yield organs. $R_{wr}(i)$ is used to predict total biomass following the yield organ initiation. Another three MPR equations are used to predict important developmental dates. These include TI , which predicts the date at which yield organ initiation is observed, $Y(TI)$, the initial dry mass of the yield organs, and TM , the date at which maturity is simulated.

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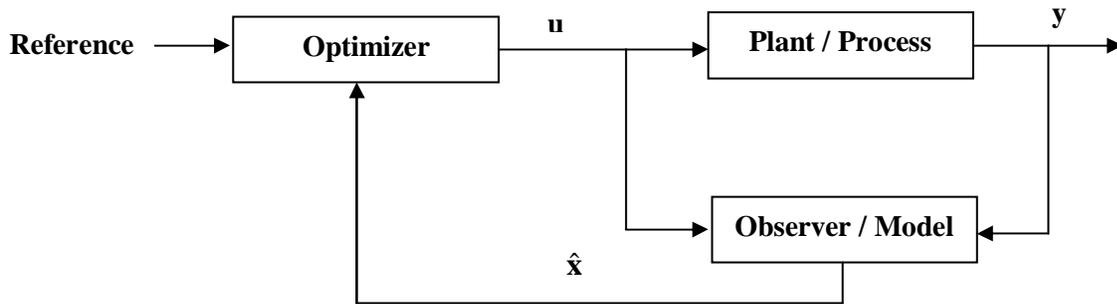


Figure 2: Model-based predictive control loop.

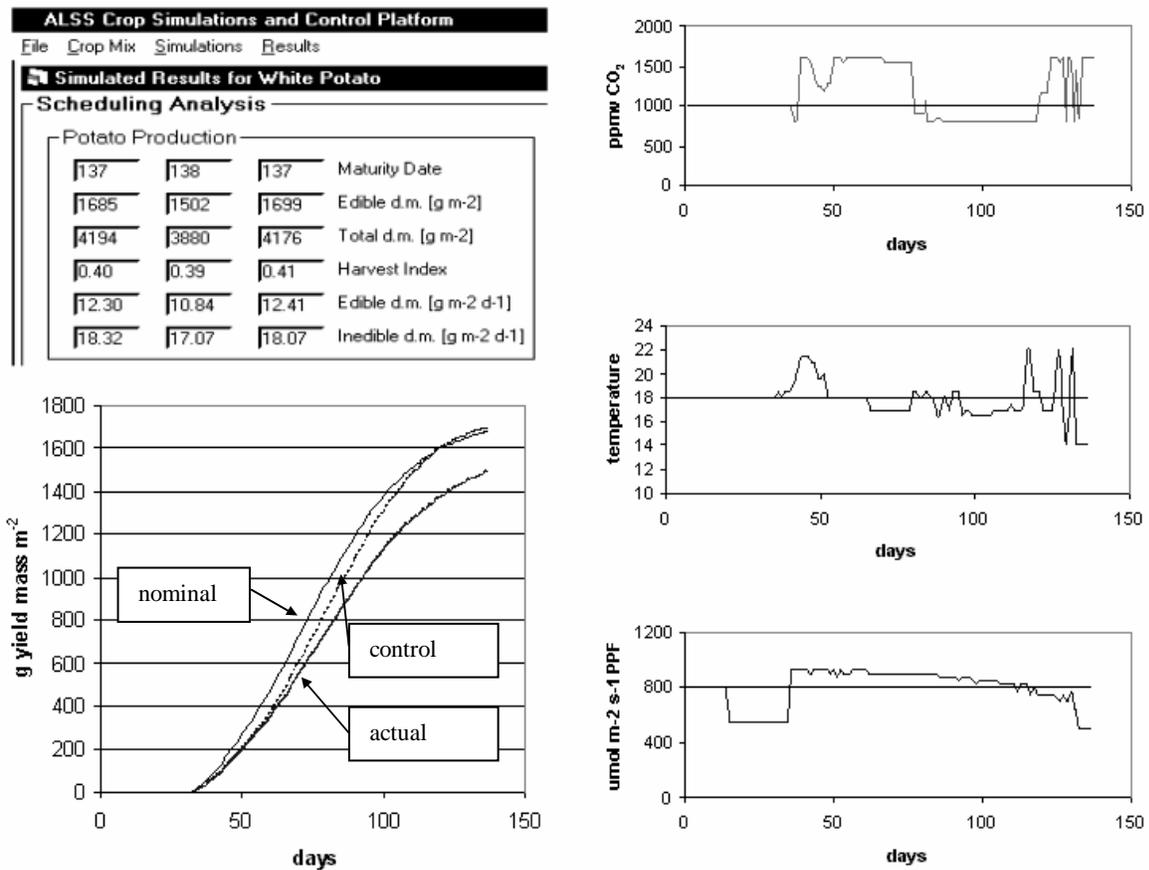


Figure 3: Model-based controller simulation. Simulated information for a -30% PPF disturbance with white potato starting at day 15 for 20 days. Clockwise starting at top left: Scheduling analysis information, where column 1 is the nominal case with no disturbance, column 2 is the case with disturbance and no control, and column 3 is with control; Control input time history plots for CO₂, T, and PPF, where the straight line represents the nominal setpoint; System response (yield dry mass) for the three cases.