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Adaptive two time-scale receding horizon optimal control for greenhouse lettuce cultivation



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ARTICLE INFO	ABSTRACT
Keywords:	A two time-scale, receding horizon, optimal controller for greenhouse lettuce cultivation is extended with on-line
Greenhouse cultivation	parameter estimation to handle ill-known or time-varying parameters of the greenhouse-crop model. By means
Adaptive control Receding horizon optimal control Time-scale decomposition	of simulations, the possible improvement of performance and reduction of constraint violation, introduced by
	this extension, are investigated. Moreover, uncommon issues in the adaptive controller design due to the two
	time-scales are considered and handled in this paper. The estimated parameters are selected based on their
	uncertainty and performance sensitivity. Using a recently developed very efficient algorithm, the selected
	parameters are checked for identifiability first. Finally the possibility of real-time implementation of the
	adaptive two time-scale receding horizon optimal controller is investigated.

1. Introduction

Greenhouses for crop cultivation provide shelter for crops to grow under unfavourable external weather. Also they enable growers to manipulate the greenhouse climate in order to increase quality and production (van Straten et al., 2010). Therefore the greenhouse industry is growing fast nowadays. In modern greenhouses, automatic control is replacing manual control. This cuts down the labour cost and increases management efficiency. However, the majority of these automatic controllers use set-points. These set-points are generally selected in a heuristic way based on rules of thumb and grower experience. These have resulted in a very large number (hundreds) of controller settings that are not transparent. Only some of these (roughly 10–20) are used by the grower while the rest remains at default values tuned or selected by the manufacturer. In practice, different growers often use different controller settings and associated values (van Straten et al., 2000).

As opposed to this, optimal control of greenhouse cultivation is a transparent, quantitative, model-based approach that is optimal in principle. This approach exploits scientific knowledge concerning greenhouses, crops and weather predictions to maximize profit. The scientific knowledge concerning greenhouses and crops is captured in a dynamic model. Profit is calculated from costs associated with greenhouse management, such as energy costs, as well as revenues obtained from selling crops. Knowledge of weather predictions and their uncertainty is used to estimate the model state on-line which in turn enables on-line optimal control. (van Straten, 2013).

Despite its favourable properties, optimal control of greenhouse cultivation still suffers from several problems. These relate to different time scales and rapidly fluctuating uncertain weather that acts as an external input (van Willigenburg et al., 2000). A major contribution in overcoming these problems, by means of time-scale decomposition and receding horizon optimal control, was made by van Henten (1994), see also van Henten and Bontsema (2009). Tap (2000) used and further developed this method for on-line implementation. A similar more recent contribution is by Gonzales et al. (2014). In this paper the method used by these authors is extended with on-line parameter estimation to investigate the possible improvement of performance and reduction of constraint violation. The estimated parameters are selected based on their uncertainties as well as the sensitivities of the controller performance (profit) to these parameters. Moreover the selection is guided by a recently developed very efficient algorithm that computes identifiability of to be estimated parameters for nonlinear systems. A different but related approach to determine such parameters is presented by Ioslovich (2004).

Past research reveals the importance of estimating uncertain model parameters on-line in greenhouse cultivation. Udink ten Cate and van de Vooren (1978), Udink ten Cate (1983), Davis (1984) and Hooper and Davis (1985) proposed and investigated adaptive control of greenhouse temperature through heating and ventilation based on a simplified model and PID control. Berenguel (2003) studied mixed feed-forward adaptive control. Arvanitis et al. (2000) proposed a scheme of multirate

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Received 25 August 2017; Received in revised form 29 January 2018; Accepted 1 February 2018 Available online 09 February 2018 0168-1699/ © 2018 Elsevier B.V. All rights reserved. adaptive temperature control between pole-placement and linear quadratic regulation. Cunha (2006) realized real-time adaptive control for greenhouse heating, cooling and CO₂ enrichment. Rodríguez (2008) put forward a strategy of adaptive hierarchical control to keep humidity in a specific range through adapting temperature set-points. Speetjens (2008) and Speetjens et al. (2009) implemented an extended Kalman filter for on-line estimating model parameters to control the so called Watergy greenhouse.

To the best of our knowledge adaptive receding horizon optimal control incorporating a two time-scale decomposition has never been considered for greenhouse cultivation. Starting from a two time-scale receding horizon optimal controller this paper investigates improvement of control performance and reduction of state constraint violation achieved by adding on-line parameter estimation to this controller. The computational effort required by the adaptive two time-scale receding horizon optimal controller is also investigated to judge the possibility of real-time implementation on a personal computer.

2. Materials and methods

2.1. Greenhouse-crop model

Given our research goals stated in the introduction, and the fact that even well-established crop models and physical models of the greenhouse lack high accuracy (Ioslovich et al., 2009), for both we prefer a relatively small white box model. Such a greenhouse-crop model was presented by van Henten (2003). This model captures the main features of the greenhouse, crop and economics to enable on-line adaptive optimal control. Moreover, to allow for a proper understanding and interpretation, a white box model is preferred.

To further motivate our model choice several candidate models from the literature are discussed shortly. The greenhouse-crop model of Tap (2000) contains a so called 'big leaf, big fruit' reduced model of tomato, that described harvest throughout the season. We prefer a single harvest crop because it is more simple from an optimal control perspective.

Van Ooteghem (2007) models an advanced Dutch solar greenhouse. Compared to conventional Dutch greenhouses additional equipment is installed to promote energy efficiency. To model this equipment a significant number of additional states and smoothed switching functions are required, complicating the dynamics. Moreover this advanced greenhouse structure served a feasibility study. Up to now it is not used in practice.

The model used by van Beveren et al. (2015) is one for minimizing energy related to both heating and cooling of a greenhouse. It doesn't include a crop model because it takes greenhouse climate trajectories as an input. Also, cooling systems are still uncommon in greenhouses.

An interesting approach to greenhouse climate control is proposed by Ioslovich et al. (2009). They use a very large and well established tomato crop model (TOMGRO) while considering the greenhouse climate partly static. To enable optimal control they furthermore rely on a series of simplifying assumptions enabling partly analytical solutions of the optimal control problems. As opposed to this, one of our research goals is to investigate whether adaptive optimal control, including a time-scale decomposition, can be applied without making any simplifying assumptions. This is motivated by the fact that optimal control algorithms are increasingly well developed, user friendly and efficient (Tomlab, Rutquist and Edvall, 2010). They allow for on-line computations for processes that are not very fast, such as greenhouse climate (van Beveren et al., 2015).

The greenhouse-crop model of van Henten (2003), used in this paper, has three states being greenhouse temperature X_T , humidity X_h , and CO₂ concentration X_c The crop, being lettuce, has only one state being crop dry weight X_d . The lettuce crops are fully harvested at the end of the growing period. Constant parameters in the model are denoted by *c* with an associated subscript. *U* indicates a control variable,

V an external weather variable while subscripts *T*, *h*, *c*, *q*, and *v* indicate respectively temperature, humidity, CO_2 , heat, and ventilation. The differential equations representing the model are,

$$\frac{dX_d}{dt} = c_{\alpha\beta}\varphi_{phot,c} - c_{resp,d}X_d 2^{(0.1X_T - 2.5)}$$
(1)

$$\frac{dX_c}{dt} = \frac{1}{c_{cap,c}} \left[-\varphi_{phot,c} + c_{resp,d} X_d 2^{(0.1X_T - 2.5)} + U_c - \varphi_{vent,c} \right]$$
(2)

$$\frac{dX_T}{dt} = \frac{1}{c_{cap,q}} [U_q - Q_{vent,q} + Q_{rad,q}]$$
(3)

$$\frac{dX_h}{dt} = \frac{1}{c_{cap,h}} [\varphi_{transp,h} + \varphi_{vent,h}]$$
(4)

with,

$$\varphi_{phot,c} = (1 - e^{-c_{pl,d}X_d}) \frac{c_{rad,phot}V_{rad}(-c_{co_{2,1}}X_T^2 + c_{co_{2,2}}X_T - c_{co_{2,3}})(X_c - c_{\Gamma})}{c_{rad,phot}V_{rad} + (-c_{co_{2,1}}X_T^2 + c_{co_{2,2}}X_T - c_{co_{2,3}})(X_c - c_{\Gamma})}$$
(5)

$$\varphi_{vent\,c} = (U_v + c_{leak})(X_c - V_c) \tag{6}$$

$$Q_{vent,q} = (c_{cap,q,v}U_v + c_{ai,ou})(X_T - V_T)$$
⁽⁷⁾

$$Q_{rad,q} = c_{rad,q} V_{rad} \tag{8}$$

$$\varphi_{transp,h} = (1 - e^{c_{pl,d}X_d}) c_{v,pl,ai} \left(\frac{c_{v,1}}{c_R(X_T + c_{T,abs})} e^{c_{v,2}X_T/(X_T + c_{v,3})} - X_h \right)$$
(9)

$$\varphi_{vent,h} = (U_c + c_{leak})(X_h - V_h) \tag{10}$$

As to the two time-scale decomposition, X_d is the slow state, while X_c , X_T , and X_h are fast states describing greenhouse climate. For further details, such as the subscripts of the constant model parameters and their corresponding values, and the physical meaning of variables, see van Henten (2003).

To apply the time-scale decomposition, a state-space representation of the model in which the fast and slow parts of the dynamics are distinguished, is convenient. To that end define the systems full state vector,

$$x = \begin{bmatrix} X_d \\ X_c \\ X_T \\ X_h \end{bmatrix}$$
(11)

the "slow state" vector corresponding to the slow dynamics,

$$x_s = X_d \tag{12}$$

and the "fast state" vector corresponding to the fast dynamics,

$$x_f = \begin{bmatrix} X_c \\ X_T \\ X_h \end{bmatrix}$$
(13)

the control input vector,

$$u = \begin{bmatrix} U_c \\ U_q \\ U_\nu \end{bmatrix}$$
(14)

and finally the vector of external inputs,

$$d = \begin{bmatrix} V_{rad} \\ V_T \\ V_c \\ V_h \end{bmatrix}$$
(15)

In state-space form the full system dynamics then read,

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