15th Triennial World Congress, Barcelona, Spain

PREDICTIVE CONTROL FOR THE OPTIMIZATION OF STEAM SOIL DISINFESTATION

Fabrizio Dabbene [*] **Paolo Gay** [**] **Cristina Tortia** [**]

[*] *IRITI - CNR*
Politecnico di Torino
corso Duca degli Abruzzi 24, Torino - Italy
dabbene@polito.it
[**] *Dipartimento di Economia e Ingegneria Agraria*
Forestale e Ambientale
Università degli Studi di Torino
via Leonardo da Vinci 44, Grugliasco (TO) - Italy
gaypaolo@agraria.unito.it,
tortia@agraria.unito.it

Abstract: Soil disinfestation by steam is an agricultural technique that is nowadays attracting growing interest for its low ecological impact and could therefore become a viable alternative to methyl bromide, that will soon banned. The current main limitation of this treatment is due to the cost of the fuel used to generate the steam.
In this paper, we present a control strategy that allows to minimize fuel consumption by optimizing the time of steam soil exposure. The effectiveness of the proposed techniques has been tested using real data collected from experiments performed in a farm in the Liguria Italian region.

Keywords: Agriculture, Mathematical models, Control

1. INTRODUCTION

In these years an alternative to methyl bromide (CH_3Br), a fumigant used to treat the soil to control plant pathogens, nematodes and weed seeds, has to be found because of its toxicity and its contribution to the Earth's ozone layer depletion, see e.g. (U.S. Environmental Protection Agency, 1997). Several European countries have already stated the complete banning of methyl bromide and Italy must progressively reduce the consumption till the prohibition in the year 2005.

Steam disinfestation, a method early used for this purpose, is environmental friendly, leaving no chemical residues or fumes toxic to the operators or the final consumers. The most diffused technique to apply steam is to cover the soil with a PVC sheet sealed at the edges (Mulder, 1979). Steam is then blown under the sheet and left to penetrate the soil. Depending on the crop grown and the pathogens resistance to pasteurization, temperature and time of exposure at different depths must be varied (Lawrence, 1956). Because of the lack of knowledge of the heat level achieved by the soil at different depths, steam is often applied for a longer period than required. While this technique is now economically affordable in the case of high profit cultures, for a large scale use the cost of the treatment, mainly due to high fuel consumption, must be reduced at minimum. Nowadays, the process is manually controlled and the decisions regarding exposition times are left to the expertise of the operators, usually leading to an inefficient use of energy. Moreover, to achieve the best disinfestation results, steam must be applied immediately before crop seeding, and in that period the treatment could take place day and night. Hence, an automation of the process would result in a save of both energy and man power. Aim of this study is to devise a prediction-based control strategy that allows to minimize the time of exposure, leading to a complete automatization of the disinfestation process. The control is based on the linear parameter varying (LPV) model of the steam soil disinfestation system developed in (Berruto *et al.*, 2001). This model can be used to predict the temperature of the soil for the entire range of soil depths involved in the process.

Fig. 1. Steam soil disinfestation of an 80m × 5m parcel of soil. Picture taken in the Liguria farm where the data of this paper were collected.

The models presented in the paper have been identified using real data collected in a farm in the Liguria region. Measurements were taken during the treatment of several 400m^2 parcels of soil for basil production. In Figure 1, the treatment of an 80m × 5m parcel is shown. The steam is inflated under the PVC film by means of two parallel cloth hoses 80m long. The steam generator produces 2,000kg/h of steam with a consumption of 170kg of fuel per hour. In the farm, about 88,000m^2 per year are treated and the resulting cost is 0.85euro/m^2. The detailed percentage distribution of the costs is reported in Figure 2.

The paper is structured as follows: in Section 2 we introduce the process under study and we propose a dynamical model for its description. Section 3 presents the adopted control strategy, which consists of a model-based optimization scheme, while Section 4 is devoted to the presentation of the simulating results obtained on the basis of real data. Concluding remarks and future directions

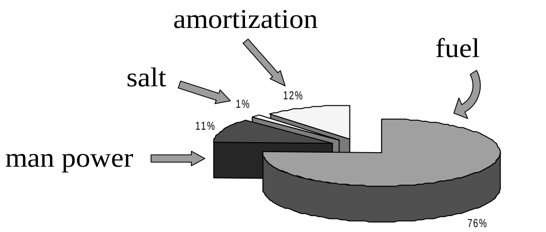

Fig. 2. Distribution of the costs for the steam soil treatment in the farm under study.

2. THE STEAM SOIL DISINFESTATION PROCESS

The steam disinfestation process of the soil can be separated in two phases. During the first one - the *heating* phase - the valve is opened and steam flows through the soil, while the second phase, referred to as *cooling*, concerns the free evolution of the system that follows the heating process. The physical phenomena involved in the two phases are quite different.

During the heating, the steam is injected under the PVC sheet by means of a cloth hose of about 80mm of diameter, longitudinally perforated. The steam expands under the PVC sheet and achieves an equilibrium that mainly depends, among others, on the steam flow rate supplied by the pipe, the partial condensation of the steam, the external temperature and the steam flux through the soil. Besides the classical dynamics that regulate the heat transport (thermal conduction, convection and radiation), this phase involves also water vapor diffusion phenomena. Since the soil parcel is covered by the film, almost all the steam flows through the soil or condensates.

In the cooling phase, water vapor diffusion, which is still present at the closing instant, progressively vanishes. The consequent difference between heating and cooling dynamics indicates a structural nonlinearity in the system. The absence of steam heat transport during cooling makes the cooling dynamics slower than the heating ones. Both depend on the depth, being heating and cooling rate faster at the surface and slowing down with increasing depth.

In actual practice, the physical modelling of these processes is very complicated and concerns combined modes and various interdependent conditions, see e.g. (Bird *et al.*, 1980; Geankoplis, 1993).

Hence, the differential equations describing the cited physical phenomena result to be very involved and inadequate for the modelling and control of actual systems (Seidman, 1996). As an example, we report in Figure 3 the temperature behavior of a section of soil of 14cm measured at six different equispaced depths during a parcel treatment in May 2001.

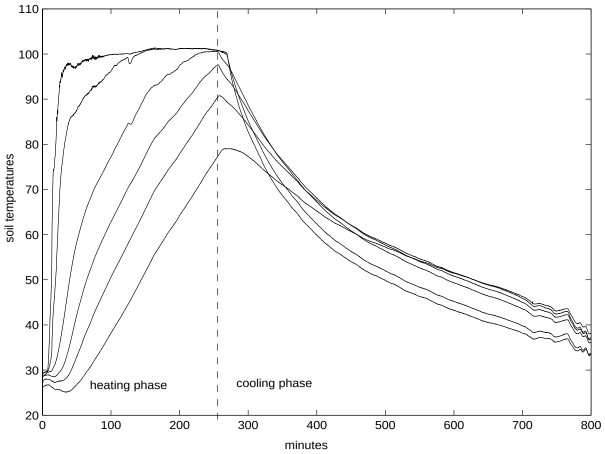

Fig. 3. Soil temperature measurements at different depths.

In (Berruto *et al.*, 2001), a simple and reliable input-output model suitable for simulation of the complete steam disinfestation process has been presented. The input of the model is the binary control signal u commanding the steam valve opening, while the output y is assumed to be the temperature of a thin slab of soil centered at a given depth ξ. This model has not been designed on the basis of physical relations, but consists of a two subsystems-based switching model. The switching command signal is driven by the closing of the steam valve. Each subsystem is designed to take care of one of the above defined phases and is described by a lumped parameter LPV discrete time model, whose coefficients depend, in a nonlinear way, on the depth ξ.

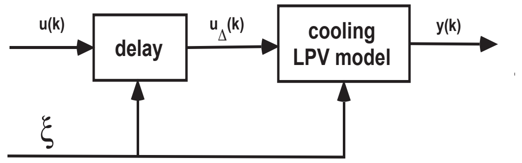

Fig. 4. Model of the cooling process.

For control purposes we consider here only the cooling subsystem since the measurements during the heating are directly collected from the the soil. The structure of the cooling subsystem is reported in Figure 4. From input-output observations an heat transport delay depending on the depth ξ was observed. Such delay has been taken into account by means of a parameter dependent delay block that affects the input signal u. The resulting delayed signal $u_\Delta(k)$ is given by

$$u_\Delta(k) = q^{-\Delta(\xi)}u(k) \qquad (1)$$

where $\Delta(\xi)$ is an unknown continuous function to be estimated and q^{-1} is the usual shift operator.

The LPV model of the cooling system is based on the following ARX dynamic model

$$A(q^{-1},\xi)y(k) = B(q^{-1},\xi)u_\Delta(k) + e(k) \ , \qquad (2)$$

with

$$\begin{aligned} &A(q^{-1},\xi) = \qquad (3)\\ &\quad 1 + a_1(\xi)q^{-1} + a_2(\xi)q^{-2} + \ldots + a_{na}(\xi)q^{-na}\\ &B(q^{-1},\xi) =\\ &\quad b_0(\xi) + b_1(\xi)q^{-1} + b_2(\xi)q^{-2} + \ldots + b_{nb}(\xi)q^{-nb} \ , \end{aligned}$$

where $y(k) = y(k,\xi)$ and the functions $a_i(\xi)$, $i = 1,\ldots,na$, and $b_i(\xi)$, $i = 0,\ldots,nb$, are to be estimated.

The model has been identified using the measurements collected in May 2001 in a Liguria region farm producing basil. Such measurements were obtained performing several soil treatments and using a transducing probe consisting of six thermocouples placed at different equispaced depth in the soil. This particular measurement system allowed to get information about the instantaneous temperature of six layers of soil at depths ranging from 1.5cm to 14cm. First, the input delay function $\Delta(\xi)$ was approximated by a cubic spline. The parameters of the spline were identified analyzing the delay in the time response to the opening valve signal by means of standard techniques.

The dynamic part of the model was then identified extracting from the process measurements the data relative to the cooling phase. The segmentation was done using the information of the estimated delay. Six models, one for any depth, have been identified.

The error in relation (2) was assumed to be unknown but bounded, that is, considering a data set of m measurements, the error vector $e \in \mathbb{R}^m$ was assumed to belong to a given membership set Ω_e

$$\Omega_e = \{e \in \mathbb{R}^m : |e(k)| \le E(k), \ \ \forall k \ \} \qquad (4)$$

where $E(k)$ is a known bounding function. With those assumptions equation (2) rewrites

$$y(k) = -\sum_{i=1}^{na} a_i(\xi)y(k-i) + \sum_{j=0}^{nb} b_j(\xi)u_\Delta(k-j) + e(k).$$

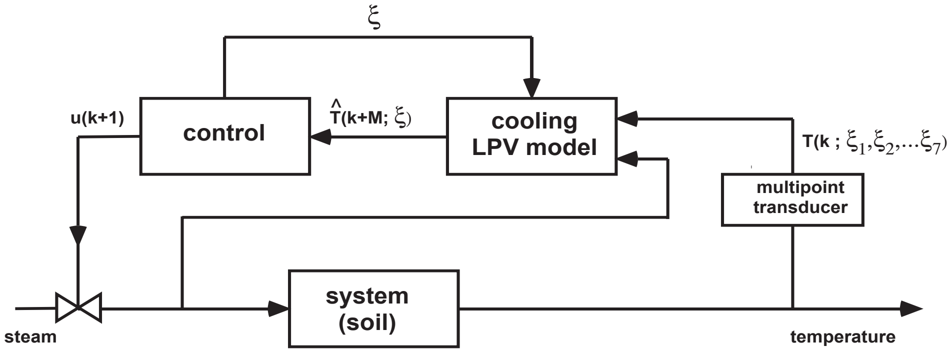

Fig. 5. Structure of the proposed control strategy.

Parameters $a_i(\xi)$, $i = 1, \ldots, na$ and $b_j(\xi)$, $j = 0, \ldots, nb$, were arranged, for notation convenience, into a single vector $\theta(\xi) \in \mathbb{R}^{np}$, $np \doteq na + nb + 1$,

$$\theta(\xi) \doteq \left[\, a_1(\xi) \;\ldots\; a_{na}(\xi) \;\, b_0(\xi) \;\ldots\; b_{nb}(\xi) \,\right]^T,$$

obtaining the regression equation

$$y = \Phi\theta(\xi) + e \qquad (5)$$

where $y \in \mathbb{R}^m$ and $e \in \mathbb{R}^m$ are the measurement and the equation error vectors, respectively, and Φ is the regression matrix, whose i-th row φ_i^T is given by

$$\varphi_i^T = \\ [-y(i-1) \cdots - y(i-na) \quad u_\Delta(i) \cdots u_\Delta(i-nb)]$$

for $i = 1, \ldots, m$. With the set membership error assumption of relation (4), the identification of the parameter vector $\theta(\xi)$ consists in finding the set $\mathcal{D}_\theta(\xi)$ of all parameter vectors θ consistent with the model (5), the measurements y and the errors e.

The corresponding parameter admissible set $\mathcal{D}_\theta(\xi)$ can be expressed as

$$\mathcal{D}_\theta(\xi) = \left\{\, \theta \in \mathbb{R}^{\,np} : y = \Phi\theta(\xi) + e, e \in \Omega_e \,\right\}.$$

In order to find a point estimate, we considered the ℓ_∞^w projection [1] estimate $\hat{\theta} \in \mathcal{D}_\theta(\xi)$, defined as

$$\hat{\theta} = \arg\min_{\theta \in \mathbb{R}^{np}} \|\Phi\theta - y\|_\infty^w \qquad (6)$$

that can be computed solving a linear programming problem involving $np+1$ variables. A proper setting of a weighting function w allowed to partially overcome the difficulties due to the weak excitation properties and the short duration of the input signal.

[1] The ℓ_∞^w norm is defined as $\|y\|_\infty^w \doteq \max_i \{w_i |y_i|\}$, $w_i > 0$

Different model orders were considered, evaluating both the one-step prediction error and, more importantly, the simulation error. The adopted orders for the final model were $na = 4$, $nb = 1$. The $a_i(\xi)$, $i = 1, \ldots, na$, and $b_i(\xi)$, $i = 0, \ldots, nb$ functions were then obtained interpolating with cubic splines the coefficients obtained identifying the model in relation (2) at the six different depths. The reader interested in further details on the model identification process may refer to (Berruto *et al.*, 2001).

3. CONTROL STRUCTURE

In order to guarantee the effectiveness of the treatment, the entire slab of soil, i.e. the soil at all depths in the operating range $\xi \in [\xi_{\min}, \xi_{\max}]$, needs to be heated to a temperature greater than T_{Tr} for at least $M\Delta t$ seconds, where Δt is the sampling period. The temperature of treatment T_{Tr} and the time of exposure $M\Delta t$ vary depending on the particular crop that will be seeded or transplanted after the disinfestation (Runia, 2000).

The minimum time of exposure, i.e. the time instant $k_c\Delta t$ of the steam valve closing, can be estimated solving the following optimization problem

$$\begin{aligned} \hat{k}_c \;&=\; \min k \qquad (7) \\ &s.t.\; k > 0 \\ &\quad \hat{T}\left(k + M - \sum_{i=0}^{k-1} I[T(i,\xi)], \xi\right) \geq T_{Tr} \\ &\quad \xi \in [\xi_{\min}, \xi_{\max}], \end{aligned}$$

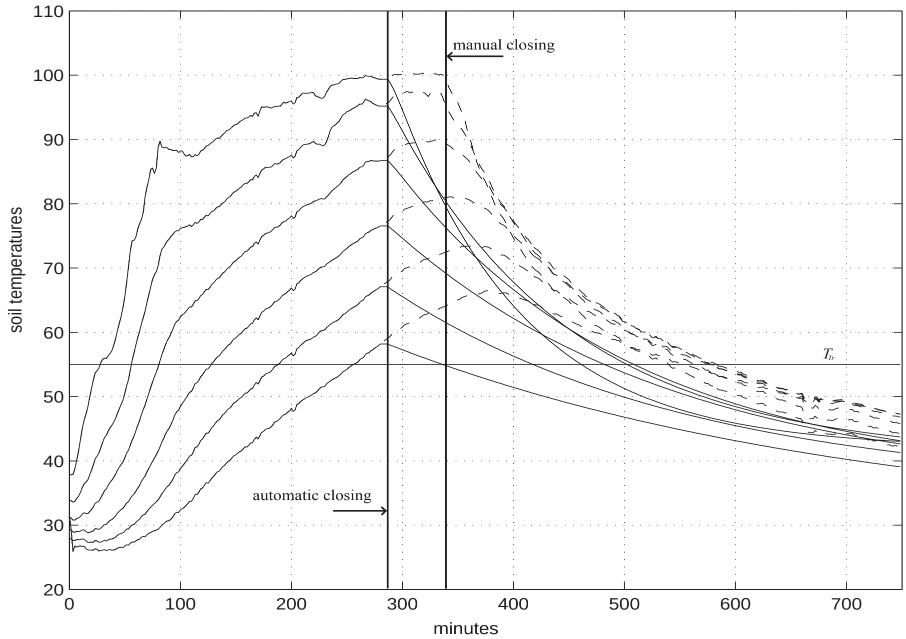

Fig. 6. Temperature behavior during treatment; - - - manually controlled and — automatic controlled. The control strategy allows to save 55 minutes of treatments, i.e. about 17% of the global costs.

where the indicator function $I[\cdot]$ is defined as

$$I[T] = \begin{cases} 1 & \text{if } T \geq T_{Tr} \\ 0 & \text{otherwise.} \end{cases}$$

In order to reduce the uncertainty introduced by the prediction $\hat{T}$ we can reduce the horizon of prediction by solving (7) on-line. This corresponds to start opening the valve and then, at any time instant k, estimate the quantity

$$\hat{T}_{\min}(k) \doteq \min_{\xi \in [\xi_{\min}, \xi_{\max}]} \hat{T}\left(k + M - \sum_{i=0}^{k} I[T(i,\xi)], \xi\right). \quad (8)$$

The valve will be closed as soon as $\hat{T}_{\min}(k) \geq T_{Tr}$. Clearly, the above control scheme requires the on-line measurement of the soil temperature. For this purpose, the same probe used to collect the data for identification may be used.

We remark that, in general, the minimization problem in (8) is not trivial, in the sense that its solution may be, in principle, not on the boundary of the domain of ξ. This is due to the fact that, during the cooling phase, the trajectories of the temperatures at different depths start from different initial conditions and are characterized by different dynamics (superficial layers heat/cool faster than deeper ones).

4. SIMULATION RESULTS

In this section, we present simulation results based on real data collected during several soil treatments performed in June 2001 in a basil farm in the Liguria region. The target of the considered treatment was to maintain a temperature $T_{Tr} = 55^o$C in a slab of soil of about 14cm for at least 75 minutes. To this aim, a standard 400m^2 parcel of soil was heated and the steam valve was closed when all the temperatures (measured by means of the transducing probe) had been above the value T_{Tr} for the required time. This corresponded to a total time of steam exposure of about 5h:36'. In particular, it was observed that, due to the long cooling phase, the temperature remained over the target threshold for further 190 minutes. Data were collected during the experiment with a sampling rate $\Delta t = 100s$ and were then used to recursively predict the optimal closing time, applying the procedure described in the previous section. Simulation shows that closing the valve after 282 minutes of treatment still guarantees the desired performance. This would result in saving about 55 minutes of treatment, i.e. a reduction of about 17% of the operational costs. Notice also that, considering the time between the instant when the temperature at all depths becomes greater than T_{Tr} and the valve closing, the proposed technique results in a reduction of about 70%.

The optimization of (8) was performed setting $T_{Tr} = 55$ and $M = 45$ and considering a grid of 50 values of ξ between 1.5 and 14. For visualization purposes, in Figure 6 we report the simulated temperature trajectories relatives to the six measured depths, superimposed to the original measurement data.

ACKNOWLEDGEMENTS

This work was partially supported by the grants of the Assessorato per l'Agricoltura of the Regione Piemonte, Italy.

5. CONCLUSIONS AND FUTURE DEVELOPMENTS

In this paper a predictive model-based control structure for the optimization of steam soil disinfestation processes has been presented. The promising results achieved by the presented control structure are encouraging its hardware implementation. We are currently designing a DSP based control device that will be tested in a large scale in-field experimental program.

REFERENCES

Berruto, R., P. Gay, P. Piccarolo and C. Tortia (2001). Grey-box models for steam soil disinfestation simulation and control. In: *Proc. of IFAC Int. Symp. on Mathematical Modelling and Simulation in Agricultural and Bio-Industries*. Haifa, Israel.

Bird, B.R., W.E. Stewart and E.N. Lightfoot (1980). *Transport phenomena*. John Wiley and Sons. New York.

Geankoplis, C.J. (1993). *Transport processes and unit operations*. Prentice-Hall. New York.

Lawrence, W.J. (1956). *Soil sterilization*. Unwin Brothers Limited. London.

Mulder, D. (1979). *Soil disinfestation*. Elsevier Scientific Public Company. Amsterdam.

Runia, W.T. (2000). Steaming methods for soil and substrates. In: *Proc. of the Int. symposium on chemical and non chemical soil and substrate disinfestations*. Torino, Italy. pp. 11–15.

Seidman, T. (1996). Control of the heat equation. In: *The Control Handbook*. IEEE-CRC Press. Boca Raton (Florida).

U.S. Environmental Protection Agency (1997). Methyl bromide use. In: *Methyl Bromide Phase Out Web Site*. Vol. http://www.epa.gov/ozone/mbr.