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Modelling and Control of Steam Soil Disinfestation Processes

F. Dabbene[1]; P. Gay[2]; C. Tortia[2]

[1]IEIIT—CNR, Politecnico di Torino, 24 Corso Duca degli Abruzzi, 10129 Torino, Italy; e-mail: fabrizio.dabbene@polito.it
[2]DEIAFA—Università degli Studi di Torino, 44 Via Leonardo da Vinci, 10095 Grugliasco (TO), Italy; e-mail of corresponding author: paolo.gay@unito.it

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Soil disinfestation by steam is an agricultural technique that recently has been attracting growing interest for its low ecological impact. The process represents a viable alternative to methyl bromide, which will soon be banned in many countries. However, high fuel costs render the treatment only economically feasible for high-profit cultures.

In this paper, a predictive control structure is presented, aimed at reducing the fuel consumption and optimising the treatment duration. The controller is based on a multiple linear parameter varying switching dynamic model that describes the soil temperature at different depths during sheet steam disinfestation. This fairly new approach allows the construction of simple models, thus overcoming the complexity introduced by physical equations.

1. Introduction

Soil disinfestation from plant pathogens, weed seeds and nematodes in intensively exploited soils is in general performed via fumigation with methyl bromide (CH_3Br). The use of this gas will soon be prevented due to its toxicity and because of its contribution to the depletion of the Earth's ozone layer.

Host plant resistance, crop rotation, biological control (use of antagonist fungi), treatment with other chemicals and solarisation represent possible alternative solutions. However, the use of steam, which leaves no toxic residues in the soil and on the crop, is nowadays more attractive. This technique may lead to a sustainable agriculture which combines the speed of application with effectiveness and immediate availability of technology. However, the main drawback of this treatment is the cost, primarily due to the high fuel consumption (up to 70–80% of total costs).

The most common technique of steam application is sheet steaming, which involves covering the soil with a thermoresistant sheet sealed at the edges and then blowing the steam under the sheet so that the steam penetrates through the soil.

The efficacy of this method relies on both soil- and host-dependent factors. Soil-dependent factors include soil type, mineralogical composition, texture, porosity, humidity and type of soil tillage. These factors affect heat transport phenomena. Host-dependent factors include microbial and weed seeds resistance to pasteurisation.

Currently, all the process phases are controlled manually and the decisions regarding exposure times are left to the expertise of operators. Due to lack of knowledge on the behaviour of soil temperature at increasing depths, steam is usually applied for fixed and arbitrary periods, frequently longer than required. Nevertheless, there are cases in which the established time of exposure is not sufficient to reach the pasteurisation of soil.

The aim of this paper is to develop a model for describing and predicting the temperature behaviour of the soil during steam disinfestation processes and to design a prediction-based control structure. Its implementation would lead to the reduction of fuel consumption by optimising the time of exposure.

Biological mechanisms, natural, environmental and agricultural systems are intrinsically complex and the mathematic description of their internal physical

Notation

$A_c(q^{-1};\xi)$	regressor of auto regressive part of ARX cooling subsystem at depth ξ	nph	size of $\theta_h(\xi)$
$A_h(q^{-1};\xi)$	regressor of autoregressive part of ARX heating subsystem at depth ξ	$Q(k;\xi)$	number of time steps up to kth instant in which the soil temperature at depth ξ is over the target temperature T_t
$a_{c_i}(\xi)$	ith coefficient of $A_c(q^{-1};\xi)$, function of depth ξ	q^{-1}	unitary shift operator
		$q^{-\Delta(\xi)}$	shift operator of $\Delta(\xi)$ steps
$a_{h_i}(\xi)$	ith coefficient of $A_h(q^{-1};\xi)$, function of depth ξ	$\cdot^{\mathrm{T}}$	transpose operator
$B_c(q^{-1};\xi)$	regressor of moving average part of ARX cooling subsystem at depth ξ	$T(k;\xi)$	soil temperature of a slab of soil at depth ξ and time instant k
$B_h(q^{-1};\xi)$	regressor of moving average part of ARX heating subsystem at depth ξ	$\hat{T}(k;\xi)$	predicted temperature at depth ξ and time instant k
		T_0	initial soil temperature
$b_{c_i}(\xi)$	ith coefficient of $B_c(q^{-1};\xi)$, function of depth ξ	$T_c(k;\xi)$	temperature of cooling subsystem at depth ξ and time instant k
$b_{h_i}(\xi)$	ith coefficient of $B_h(q^{-1};\xi)$, function of depth ξ	$T_h(k;\xi)$	temperature of heating subsystem at depth ξ and time instant k
$D_{\theta_h}(\xi)$	membership set of vector $\theta_h(\xi)$ at depth ξ	δt	sampling time
$E(k)$	error bound at time instant k	$u(k)$	binary steam valve opening control signal at time instant k
e	measurement error vector		
$e(k)$	measurement error at time instant k	$u_\Delta(k)$	delayed binary steam valve opening control signal at time instant k
$I[\cdot]$	threshold function		
k	time instant index	$\Delta(\xi)$	heat transport delay at depth ξ
k_c	optimal closing time instant	$\theta_c(\xi)$	parameter vector of cooling subsystem at depth ξ
$\hat{k}_c$	optimal closing time instant estimated by Algorithm 1	$\theta_h(\xi)$	parameter vector of heating subsystem at depth ξ
k_{stop}	time instant of valve closing during manual treatment	ξ	soil depth
$k^*(\xi)$	switching instant of LPV model at depth ξ	$[\xi_{min},\xi_{max}]$	interval of depths considered for treatment optimisation
nac	degree of $A_c(q^{-1};\xi)$		
nah	degree of $A_h(q^{-1};\xi)$	Φ_h	regressor matrix of ARX heating subsystem
nbc	degree of $B_c(q^{-1};\xi)$		
nbh	degree of $B_h(q^{-1};\xi)$	φ_i^{T}	ith row of Φ_h
npc	size of $\theta_c(\xi)$	Ω_e	membership set of error vector e

properties can be difficult. The model proposed in this paper follows a fairly new approach. Instead of relying on physical-based models (usually highly complex and non-linear), the new approach is based on a lumped parameter single-input single-output, linear parameter varying (LPV) dynamic model that directly relates the input signal of the steam valve switch with soil temperature at different depths.

2. Methods

Soil temperature data were taken in May 2001 during the treatment in open field in a Liguria farm where 90 000 m^2 of soil are treated each year by sheet steaming before basil cultivation. The soil is cultivated for sowing and prepared in 400 m^2 parcels (80 m long, 5 m wide), which are divided in three ridges. Steam is blown under the sheet by two parallel cloth hoses of 80 mm diameter placed in the trenches between the ridges. Each cloth hose is connected to a valve by which it is also possible to inflate air by means of a Venturi inlet.

The covering sheet is a 60 µm thick fluoro-polymer foil and is sealed at the edges with soil. A boiler produces about 2000 kg h^{-1} of steam at 170°C, with a fuel consumption of 167 kg of gasoline per hour. During each treatment, in which the usual practice lasts 4–6 h per parcel, the boiler output is directly connected to the cloth hoses through an on–off valve. This direct coupling necessitates the synchronisation of the closure of the valve of a parcel with the opening of the valve of the next parcel.

Thin cylindrical probes equipped with thermocouples sensors at six different depths (15, 40, 65, 90, 115,

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

140 mm) were placed in several points of the parcel during steam soil disinfestation. Measurements were collected with a sampling cadence δt of 5 s using National Instruments FP2000 and Advantech 5510 dataloggers.

The actual data used for model identification presented in this paper were taken in a parcel with a 9·7% initial soil moisture during a 6-h treatment. The reported humidity has been computed averaging five samples of soil collected at 10 cm depth.

A picture of this treatment is reported in *Fig. 1*. The sets of data used for validation were collected in adjacent fields.

3. Process modelling

3.1. *Process description*

The steam disinfestation process of the soil can be separated in two phases. In the first, referred to as the heating phase, the boiler valve is open and steam is supplied to the soil. The second phase, referred to as cooling, concerns the free evolution of the system following the heating process. The physical phenomena involved in the two phases are quite different.

During the heating phase, water vapour diffusion phenomena occur in addition to the classical dynamics that regulate the heat transport (thermal conduction, convection and radiation). In fact, the steam at 170°C is allowed to flow in the cloth hoses and progressively expands due to atmospheric pressure. The pressure developed under the sheet depends mainly on steam flow rate supplied by the pipe, partial condensation of the steam, air and soil temperature, steam flux through the soil, weight and resistance due to the elastic deformation of the sheet. Almost all the supplied steam either flows through the soil or condenses. The amount lost to the outside environment is negligible. When the sheet is fully inflated, as shown in *Fig. 1*, the resulting pressure under the sheet makes the steam diffusion through the soil quite homogeneous. Since the parcels subject to heating are sufficiently large, boundary effects can be neglected and the temperature of soil can be assumed to be dependent, from a geometrical point of view, mainly on the depth. Data collected during preliminary experiments in different positions under the sheet validate this conjecture.

In the cooling phase, water vapour diffusion, which is still present at the time of closure of the valve, progressively vanishes. The consequent difference between heating and cooling dynamics indicates a structural non-linearity in the system. The absence of steam heat transport during this phase makes the cooling dynamics slower than the heating ones. Both dynamics depend on the depth since heating and cooling rates are faster at the surface and slow down with increasing depth.

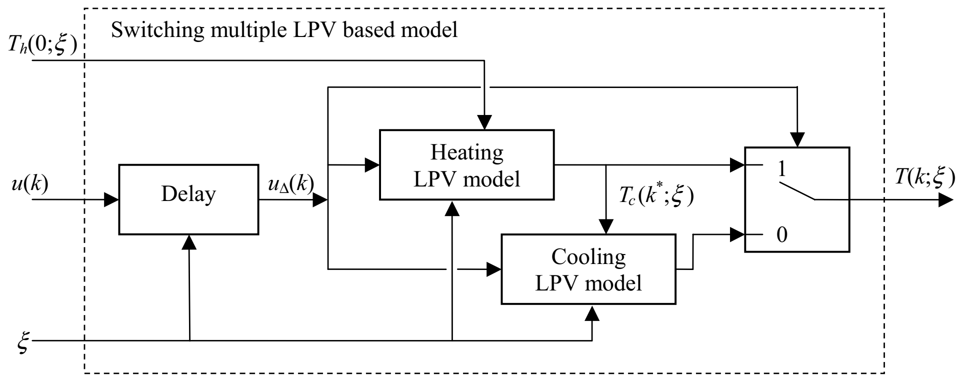

Fig. 2. The switching linear parameter varying (LPV) model: u(k), binary valve command signal; ξ, soil depth; $u_\Delta(k)$, delayed input signal; $T_h(0;\xi)$, initial soil temperature at depth ξ; $T_c(k^*;\xi)$, soil temperature at the switching instant k^* at depth ξ; $T(k;\xi)$, output of the model (estimated temperature of the soil at time instant k and depth ξ)

The partial condensation of the steam during the supply increases the quantity of water in the soil. This occurrence affects the thermal and physical properties of soil, making the system non-stationary.

Finally, the dynamics that regulate heat transport depend on soil characteristics like texture, composition and porosity and, further, on type of tillage and initial humidity.

The physical modelling of the whole process concerns combined modes and various inter-dependent conditions (Bird *et al.*, 1960; Geankoplis, 1993; Moyls, 1994) that immediately lead to heavily involved non-linear distributed parameter equations. These could be very critical in the identification of the model and the subsequent control design (Abu-Hamdeh, 2001; Abu-Hamdeh *et al.*, 2000; Seidman, 1996; Van Donk & Tollner, 2000). Moreover, some of the modelled phenomena could not be singularly observable, and so identifiable, from input–output data (Russel, 1996).

3.2. *The switching linear parameter varying model*

With the aim of designing and implementing a control structure for the steam supply optimisation, an input–output model able to predict the soil temperature at different depths has been constructed. To allow on-line prediction, computational complexity has been minimised by adopting a lumped parameter grey-box model whose input u has been assumed to be the binary steam valve opening control signal, while the output T is the temperature of a slab of soil at a given depth ξ.

In order to describe the heating and the cooling dynamics, respectively, the model has been based on two switching subsystems as depicted in *Fig. 2*. Each subsystem is designed to take care of one of the previously defined phases. This technique preserves the linearity of the two single subsystems and overcomes the main non-linearity of the system.

The switching command signal has been assumed to be driven by the closure of the steam valve. From raw data observation, it arises that the input u and, therefore, the switching instant between the two submodels are affected by a delay that depends on the depth ξ.

Such depth-dependent delay could not be embedded in a linear model and needs to be separately described. To this extent, the delayed signal $u_\Delta(k)$ at time instant k is introduced. This signal drives both the subsystems and switch and it is given by

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

where $\Delta(\xi)$ is parameterised as a cubic spline (Wahba, 1990) and q^{-1} is the unitary shift operator.

Each of the two subsystems has been modelled by a depth-dependent lumped parameter discrete time model based on an LPV structure. LPV systems are defined as linear systems whose dynamics depend on exogenous time-varying signals, generally assumed to be confined to a prescribed set (Belforte & Gay, 2000; Rugh, 1991; Rugh & Shamma, 2000; Shamma & Xiong, 1999; Wu & Grigoriadis, 2001). This model is structurally simpler than a black-box distributed parameter model (Jaluria & Torrace, 1986; Phillipson, 1971) and will be directly suitable for control design and realisation purposes.

More rigorously, the two subsystems involved can be expressed as follows.

The LPV heating subsystem is based on the auto-regressive with exogenous input (ARX) dynamic model (Ljung, 1987):

$$A_h(q^{-1};\xi)T_h(k;\xi) = B_h(q^{-1};\xi)u_\Delta(k) + e(k) \qquad (2)$$

where

$$A_h(q^{-1};\xi) = 1 + a_{h_1}(\xi)q^{-1} + a_{h_2}(\xi)q^{-2} + \cdots a_{h_{nah}}(\xi)q^{-nah} \tag{3a}$$

$$B_h(q^{-1};\xi) = b_{h_0}(\xi) + b_{h_1}(\xi)q^{-1} + b_{h_2}(\xi)q^{-2} + \cdots + b_{h_{nbh}}(\xi)q^{-nbh} \tag{3b}$$

are the two regressors.

The parameters $a_{h_i}(\xi)$, $i=1,\ldots, nah$, and $b_{h_i}(\xi)$, $i=0,\ldots, nbh$, are unknown (continuous) functions of the depth ξ and are to be estimated. Also in this case, functions $a_{h_i}(\xi)$ and $b_{h_i}(\xi)$ have been parameterised as cubic spline functions.

The structure of the cooling subsystem is similar, that is

$$A_c(q^{-1};\xi)T_c(k;\xi) = B_c(q^{-1};\xi)u_\Delta(k) + e(k) \tag{4}$$

with

$$A_c(q^{-1};\xi) = 1 + a_{c_1}(\xi)q^{-1} + a_{c_2}(\xi)q^{-2} + \cdots + a_{c_{nac}}(\xi)q^{-nac} \tag{5a}$$

$$B_c(q^{-1};\xi) = b_{c_0}(\xi) + b_{c_1}(\xi)q^{-1} + b_{c_2}(\xi)q^{-2} + \cdots + b_{c_{nbc}}(\xi)q^{-nbc} \tag{5b}$$

where, again, the functions $a_{c_i}(\xi)$, $i=1,\ldots, nac$, and $b_{c_i}(\xi)$, $i=0,\ldots, nbc$, are to be estimated.

The switching subsystem is driven by the delayed binary signal $u_\Delta(k)$ and generates the final output $T(k;\xi)$ according to the following relation:

$$T(k;\xi) = \begin{cases} T_h(k;\xi) & \text{if} \quad u_\Delta(k) = 1 \\ T_c(k;\xi) & \text{if} \quad u_\Delta(k) = 0 \end{cases} \tag{6}$$

3.3. *Model identification and validation*

As different types of soils have different thermodynamic properties, a set of models, one for each type of soil, should be theoretically identified. However, the physical characteristics of the various soils considered in this paper are sufficiently similar to allow the identification of a single model for their description.

Initial water content and type of soil tillage, that affect thermal response (Lawrence, 1956), could also be optimally set (*i.e.* controlled and normalised) according to well-established criteria that take into account variables such as crop requirements and weather conditions.

Due to the increasing water content during steam supply, the above-mentioned non-stationary behaviour of the system restricts the design of the input signal u used for identification. For this reason, to obtain a reliable model the system needs to be identified at the same operating conditions of actual disinfestation treatments. This leads to the following gate input signal for the identification, that has the same structure of the signal actually used during disinfestations:

$$u(k) = \begin{cases} 0, & k \leqslant 0 \\ 1, & 1 \leqslant k \leqslant k_{stop} \\ 0, & k > k_{stop} \end{cases} \tag{7}$$

Unfortunately, this input signal has a poor spectral content, and in most cases the short duration of the valve opening phase (k_{stop} steps) does not allow the system to reach steady state at all depths.

For validation purposes, experimental data have been first divided in two subsets. The first one, used for the identification of the two LPV models, consisted in the temperature measurements at the depths 15, 40, 65, 115 and 140 mm. The measurements at 90 mm were not used in the identification phase and were left out for validating the correctness of the identified model.

It should be pointed out that, in actual practice, data are affected by systematic and class errors of the measurement equipment and by rounding and truncation errors of the digital devices. Therefore, standard identification methods (*e.g.* Ljung, 1987) that require the introduction of *a priori* statistical hypotheses on the measurement error $e(k)$ in relations (2) and (4) are hardly applicable. A worthwhile alternative to the stochastic description of measurement errors is the bounded-error characterisation where the uncertainties are described in terms of tolerances or more generally as belonging to given membership sets (Walter & Piet-Lahanier, 1990; Belforte *et al.*, 1990).

In this context, the error is assumed to be point-wise unknown but bounded so that when expressed as an error vector $e \in \Re^m$, it belongs to a membership set Ω_e defined as

$$\Omega_e = \{e \in \Re^m : |e(k)| \leqslant E(k), \forall k\} \tag{8}$$

where $E(k)$ is a known and user-defined bounding function.

The first step of the identification process concerns the estimation of the input delay function $\Delta(\xi)$. This can be performed by estimating the delay at each single depth by means of standard techniques (*e.g.* Ljung, 1987) and then by interpolating the delays at different depths with a cubic spline.

The second step, the data allocation, consists of splitting the identification measurements into two sets, one for the identification of each subsystem. The first set, referred to as heating data set, consists of the measurements collected during steam supply, *i.e.* from the valve opening time to the valve closing time, shifted according to the corresponding above estimated delays. The cooling data set contains measurements collected during the free evolution of the system following the heating phase.

For any subsystem, five models, one for each depth, have been identified. Concerning the heating subsystem, Eqn (2) could be rewritten in regression form as

$$T_h(k;\xi) = \sum_{i=1}^{nah} a_{h_i}(\xi) T_h(k-i;\xi) + \sum_{j=0}^{nbh} b_{h_j}(\xi) u_\Delta(k-j) + e(k) \quad (9)$$

while parameters $a_{h_i}(\xi)$, $i=1,\ldots,nah$, and $b_{h_j}(\xi)$, $j=0,\ldots,nbh$, can be arranged for notation convenience into a single vector $\theta_h(\xi) \in \Re^{nph}$:

$$\theta_h(\xi) = \lfloor a_{h_1}(\xi) \ldots a_{h_{nah}}(\xi) \quad b_{h_0}(\xi) \ldots b_{h_{nbh}}(\xi) \rfloor \quad (10)$$

with $nph = nah + nbh + 1$. Hence, considering m consecutive measurements, Eqn (9) can be compactly expressed in matrix form as

$$T_h(\xi) = \Phi_h \theta_h(\xi) + e \quad (11)$$

where: $T_h(\xi) \in \Re^m$ and $e \in \Re^m$ are the measurement and the equation error vectors, respectively, and $\Phi_h \in \Re^{m \times nph}$ is the regression matrix, whose *ith* row φ_i^{T} is given by

$$\begin{aligned} \varphi_i^{\mathrm{T}} = [&-T_h(i-1;\xi) \ \ldots \ -T_h(i-nah;\xi) \\ &u_\Delta(i) \ \ldots \ u_\Delta(i-nbh)] \end{aligned} \quad (12)$$

With the set membership error assumption of Eqn (8), the identification of the system consists in finding the set $D_{\theta_h}(\xi)$:

$$D_{\theta_h}(\xi) = \left\{ \theta \in \Re^{nph} : T_h(\xi) = \Phi_h \theta_h(\xi) + e, e \in \Omega_e \right\} \quad (13)$$

of all parameter vectors θ_h consistent with model (11), the measurements T_h and the errors e.

Even if any point $\theta_h \in D_{\theta_h}(\xi)$ validates the model and can be assumed as a possible estimate, some point estimate algorithms that satisfy different optimality criteria can be found in literature (*e.g.* Tempo, 1988). In this paper, the nominal model has been identified considering the l_∞^w optimal projection estimate $\hat{\theta}$ defined as

$$\hat{\theta} = \arg \min_{\theta \in D_\theta} \|\Phi\theta - T\|_\infty^w \quad (14)$$

where the l_∞^w norm is defined as $\|y\|_\infty^w \doteq \max_i \{w_i |y_i|\}$, with $w_i > 0$. Such estimate can be efficiently computed solving a linear programming problem involving $nph + 1$ variables.

The initial conditions of the heating model were chosen to correspond to the initial soil temperature T_0 in °C, *i.e.*

$$\begin{aligned} T_h(-nah+1;\xi) = \ldots = T_h(0;\xi) = T_0 = 20, \\ \forall \xi \in [\xi_{min}, \xi_{max}] \end{aligned} \quad (15)$$

A similar procedure was adopted for the identification of the cooling LPV system. However, due to the $u_\Delta(k)$ driven switching, the initial conditions of the model should correspond to the output temperatures of the heating process, *i.e.* denoting by $k^*(\xi)$ the switching instant at the ξ depth:

$$\begin{aligned} &\left[T_c\big(k^*(\xi) - nac + 1\big) \ \ldots \ T_c\big(k^*(\xi)\big)\right] \\ &= \left[T_h\big(k^*(\xi) - nac + 1\big) \ \ldots \ T_h\big(k^*(\xi)\big)\right] \end{aligned} \quad (16)$$

The consequences of the weak excitation properties and short duration of the input signal could be overcome by setting a suitable function w in Eqn (14). This could be practically performed assuming a proper bounding function $E(k)$.

4. Optimisation and control

4.1. *The control structure*

In order to guarantee the effectiveness of the treatment, the entire layer 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 higher than T_t for at least $M\delta t$ seconds, where δt is the sampling period. The temperature of treatment T_t and the time of exposure $M\delta t$ vary depending on the particular crop that will be seeded or transplanted after the disinfestations (Mulder, 1979; Runia, 2000).

At the present stage, the valve is manually closed by the operator as soon as the temperature $T(\xi)$ measured at a finite number of depths $\xi_1, \xi_2, \ldots, \xi_n$, $\xi_i \in [\xi_{min}, \xi_{max}]$, satisfies the specifications. That is all the $T(\xi_i)$, $i = 1, \ldots, n$, have been higher than T_t for at least $M\delta t$ seconds. Evidently, this procedure may be highly inefficient, since the heating of soil normally continues after the steam supply is stopped. Generally, this leads to treatment times longer than required and, therefore, to higher operational costs. To avoid this drawback, it should be feasible to predict the temperature behaviour of the entire slab of soil. The proposed controller acts using the information of the estimated temperature $\hat{T}(k;\xi)$, which is predicted by the switching multiple LPV model.

In order to formalise the control law, the following threshold function is introduced:

$$I[T(k;\xi)] = \begin{cases} 1 & \text{if} \quad T(k;\xi) \geqslant T_t \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

that indicates the feasibility of a temperature $T(k;\xi)$ with respect to the target temperature T_t.

It is easy to verify that the time of effective treatment at the time instant $k\delta t$, *i.e.* the total time in which the soil at depth ξ maintained a temperature higher than the target temperature T_t, may be expressed by $Q(k;\xi)\delta t$, being

$$Q(k;\xi) \doteq \sum_{i=0}^{k} I[T(i;\xi)] \tag{18}$$

The minimum time of exposure, *i.e.* the optimal time instant $k_c\delta t$ of the steam valve closing command, can be estimated by the solution $\hat{k}_c$ of the following optimisation problem:

$$\begin{aligned} \hat{k}_c = \quad & \min \quad k \\ & \text{s.t.} \quad k > 0 \\ & \qquad T(k;\xi) \geqslant T_t \\ & \qquad T(k+M-Q(k;\xi);\xi) \geqslant T_t \\ & \qquad \xi \in [\xi_{min}, \xi_{max}] \end{aligned} \tag{19}$$

The recursive implementation of the above optimisation problem leads to the following control algorithm.

Algorithm 1

1. $k \leftarrow 0$
2. open the valve
3. $k \leftarrow k+1$
4. if $\min_{\xi\in[\xi_{min},\xi_{max}]} T(k;\xi) < T_t$ then goto 3
5. predict the temperature $\Gamma(k)$ in the slab of soil according to

$$\Gamma(k) \doteq \min_{\xi\in[\xi_{min},\xi_{max}]} \hat{T}(k+M-Q(k;\xi);\xi) \tag{20}$$

6. if $\Gamma(k) < T_t$ then goto 3
7. close the valve
8. end

The control structure implementing Algorithm 1 is reported in *Fig. 3*. The proposed control scheme makes use of on-line measurement of soil temperature only at a small number of different depths for tracking and predicting the general behaviour of the temperature in the whole slab of soil. These measurements can be collected using the same probe used in the identification phase. The valve is closed as soon as $\Gamma(k) \geq T_t$, *i.e.* as soon as the lowest temperature in the slab is guaranteed to be maintained at a temperature higher than the target temperature T_t for at least $M\delta t$.

In general, the minimisation problem in Eqns. (19)–(20) is not trivial, that is, the solution may not be on the boundary of the domain of ξ. This is due to the fact that the trajectories of temperatures at different depths could intersect. In fact, as it can be seen in *Fig. 5*, such trajectories start from different initial conditions and are characterised by different dynamics. In general, superficial layers heat and cool faster than deeper ones.

5. Experimental results

Some numerical results have been recorded, based on real data collected from the basil field during soil treatments performed in June 2001.

The target of the treatment was to maintain a temperature $T_t = 55°C$ in a slab of soil of about 140 mm for at least $M\delta t = 75$ min. Thus, a standard 400 m^2 parcel of soil was heated and the steam valve was closed when all temperatures measured by means of the six-depth transducing probe previously described had been above the value T_t for the required time. This corresponded to a total time of steam exposure of about 5 h 36 min. In particular, it was observed that, due to the long cooling phase, the temperature remained over the target threshold for further 190 min.

A model identification procedure was carried out using the techniques presented earlier, leaving out the

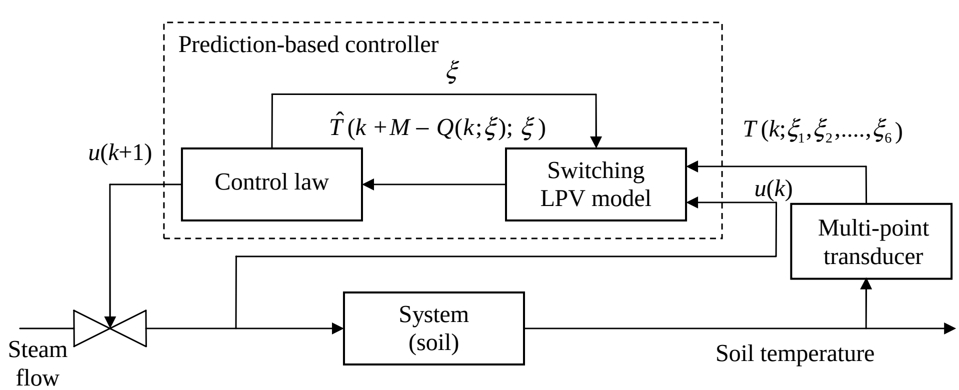

Fig. 3. Structure of the prediction model-based control system: u(k) and u(k+1), binary valve command signal at time instants k and k+1, respectively; ξ, soil depth; Q(k; ξ), number of time steps up to kth instant in which the soil temperature at depth ξ is over the target temperature T_t; $\hat{T}(k+M-Q(k;\xi);\xi)$, estimated soil temperature at instant $k+M-Q(k;\xi)$ and depth ξ; M, exposure time of the soil at the target temperature expressed as number of time steps

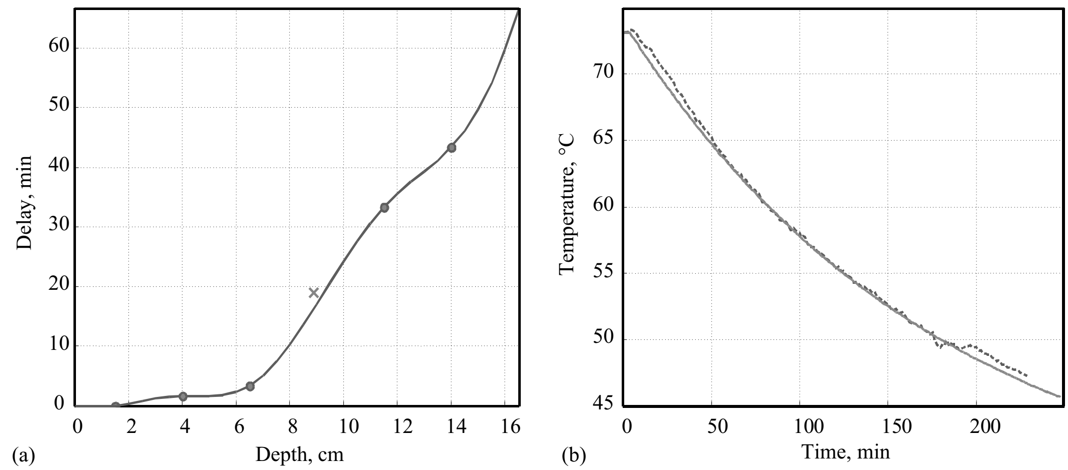

Fig. 4. (a) Behaviour of the input delay as a function of the depth: ×, measured delay at ξ=90 mm; (b) validation of the linear parameter varying cooling subsystem, measured (dashed blue line) and simulated (solid red line) data for ξ=90 mm

temperature information relative to the depth of 90 mm for validation purposes.

First, the delays at the specified depths were estimated using standard methods. The function $\Delta(\xi)$ was obtained via spline interpolation. Then, different model orders for the ARX dynamic models of the LPV subsystems were considered evaluating both the one-step prediction error and the simulation error. The adopted orders for the final models were $nah=4$, $nbh=1$ for the heating subsystem and $nac=4$, $nbc=1$ for the cooling subsystem. These orders lead to a good compromise between model complexity and approximation performances.

The $a_{h_i}(\xi)$, $i=1,\ldots,nah$, and $b_{h_i}(\xi)$, $i=0,\ldots,nbh$ functions for the heating subsystem were then obtained by interpolating with cubic splines the coefficients obtained identifying models in relations (2) and (4) at the five different depths. A similar procedure was used for the cooling subsystem.

The generalisation features of the identified model were evaluated by using the obtained model to predict the delay and temperature behaviour for the depth of 90 mm. *Fig. 4(a)* and *Fig. 4(b)* show the estimated delay function and the measured and simulated cooling phase.

In order to evaluate the benefits of the proposed strategy, the proposed controller structure was applied to an actual process. The on-line application of Algorithm 1 to the measured data suggested a closing time of 255 min of treatment. This guarantees the desired performance and results in saving about 78 min of treatment, which represents a reduction of about 23% of the operational costs.

The optimisation of Eqn. (20) was performed considering a grid of 50 values $\xi_1, \ldots, \xi_{50}$ of depths ξ between $\xi_{min}=15$ mm and $\xi_{max}=140$ mm. The temperatures $\hat{T}(\cdot;\xi)$, $i=1,\ldots,50$, were estimated by the model. For visualisation purposes, *Fig. 5* reports the predicted temperature trajectories relative to the measured depths superimposed to the actual measurement data.

6. Conclusions and future developments

In this paper, a general framework for the modelling and control of the steam soil disinfestation process has been presented. In particular, the proposed model-based control structure is aimed at optimising fuel consumption during treatment. The process has been described by two depth-dependent switching LPV dynamic models. These models are based on a black-box representation and therefore do not explicitly derive from physical relations. The paper shows how the proposed parametrically efficient (parsimonious) low-order uncertain model could reflect the dominant modal characteristic of the system and can be also interpreted in physical meaningful terms. Then, a control strategy which uses the developed model for predicting the evolution of the soil temperature is proposed.

An experimental application confirmed the effectiveness of the proposed methodology. The reported experimental data show that the application of the proposed control algorithm saves 23% of treatment time, with a substantial reduction of fuel consumption. The obtained results are very promising and are

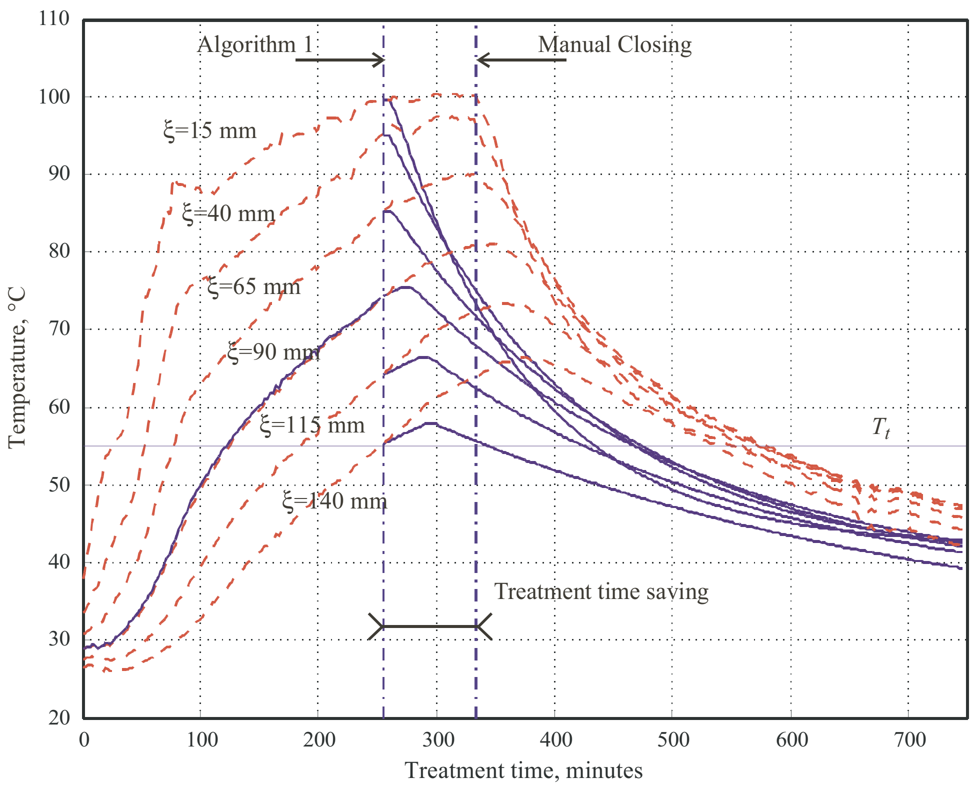

Fig. 5. Temperature behaviour during treatment; (dotted red line) manually controlled treatment; (solid blue line) automatic controlled treatment. In order to guarantee the target temperature T_t for at least 75 min in the soil at all the depths $\xi \in [\xi_{min}, \xi_{max}]$, the manual treatment lasted 336 min. The use of the control Algorithm 1 allowed to save 78 min of treatments, i.e. about the 23% of the treatment time

encouraging a commercial implementation of the proposed predictive control structure.

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