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MODEL PREDICTIVE CONTROL OF THE WATER BASED PAINTING DRYING USING A HUMIDITY PROFILE SOFT SENSOR AND A TEMPERATURE MEASUREMENT

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ABSTRACT

This paper deals with the constrained optimal control of an infrared drying process of a water based epoxy-amine painting. This approach is based on a nonlinear dynamic unidirectional diffusional model of infrared drying phenomena where both heat and mass transfers under shrinkage conditions are accounted for. The control problem is to minimize the processing time while accounting for any constraints for some of the characteristics (i.e. the temperature and the humidity profile) during the drying cycle. This is solved using a model predictive control framework where the nonlinear diffusional model is directly used in the control formulation. Such advanced controller requires the use of a soft-sensor (observer) in order to reconstruct the entire humidity profile according to the infrared flow applied, the measured temperature and the model.

INTRODUCTION

Reactive painting drying is an important industrial problem through its impact for the quality of the final aspect of products in many industries (cars, preglass plain sheets, cans, etc.). The main difficulty encountered during this operation is the evacuation of the solvent. It is needed to simultaneously build the painting film and to ensure the film polymerization but its presence has to be avoided: it has not to be trapped in the final dried product. Until recently, the use of volatile organic compounds (VOCs) allowed

the control of this evacuation during the polymerization reactions. But the enforced laws concerning environment lead now to replace the use of VOC by the use of water based solvent that evacuates less rapidly and at higher temperatures than VOC. To overcome this problem, infrared flow drying is widely developed in industrial processes. In (Okazaki et al., 1974; Vrentas et al., 1994), diffusion problems with both infrared and water used as solvent are tackled.

Model Predictive Control (MPC) or receding horizon control refers to a class of control algorithms in which a dynamic process model is used to predict and optimize process performance (Qin et al., 2003). It is widely used in industrial applications. The idea is to solve, at each sample time, an open-loop optimization problem over a finite prediction horizon in order to find the value of the manipulated variable that has to be implemented. The procedure is reiterated at the next sample time with the update of process measurements. MPC is well suited for high performance control since constraints can be explicitly incorporated into the formulation of the control problem.

In this paper, we present a MPC strategy that allows, for an infrared drying process of a water based epoxy-amine painting, to reduce the operating time while accounting for any constraints for some of the dynamic characteristics (i.e. the temperature and the humidity profile).To ensure the final product quality, paint producers propose to track a reference temperature trajectory during the drying cycle in order to extract water as best as possible before polymerization reactions starts. But the optimal control problem would rather be to minimize the operating time while directly accounting for constraints dealing with the final product quality (bubbles and fissures phenomena that can happen during the polymerization reaction have to be avoided). Such constraints are not known for the moment and would probably be based on the humidity gradient profile since it is the inner driving force during the drying. Moreover, process physical limitations such that the magnitude and the velocity of the manipulated variable have to be taken into account in the problem resolution. Such an approach was previously experimentally validated (Dufour et al., 2004) for the trajectory tracking of the measured temperature or the measured mean humidity. In this paper, the unmeasured humidity profile is needed by the MPC. This profile is therefore estimated based on a soft-sensor (observer): it uses the value of the infrared flow applied, the measured temperature and the partial differential equation (PDE) model.

The paper is organized as follow: first, the first-principles diffusional model obtained in a previous work is briefly described. Then, observer aspect is briefly discussed and the MPC strategy is detailed. Finally, simulation results are discussed.

KNOWLEDGE-BASED MODELLING

Painting formulation and characteristics

Due to the great complexity of industrial paintings, the painting is a water based epoxy-amine painting formulated in our laboratory. This permitted us to experimentally determine every physical, thermal and chemical properties (Blanc et al., 1997). The painting film is composed of two elements:

- a resin constituted of an ``oil in water" emulsion of DGEBA (Diglycidylether of Bisphenol A) which condensation index is equal to 0.15,
- a hardener composed of a primary triamine soluble in water. Currently used in the painting industry, it is named Jeffamine T403.

During the experiments, this painting film is coated in low thickness (between 30 and 300 μm) on an iron substrate (also named the support), that has been first classically treated at its surface like in the automobile industry. The painting characteristics and support characteristics can be found in details in (Blanc et al., 1997). During the drying, two phenomena occur: the solvent vaporization (the water in the present case) and the reticulation. Given the dynamic of these phenomena (respectively about 100s for the vaporization and about 100min for the reticulation in the present experimental conditions), the reticulation phenomenon is accounted for in this work. Therefore, drying characteristics depend only on

the temperature and the humidity. Moreover, a non negligible deformation of the film happens during the drying due to water content (40% of the humidity on dry basis). Given the low sample thickness with respect to its surface, this deformation phenomenon is characterized by the sample thickness variation.

Infrared dryer

The near infrared panel curing dryer used during the experiments was previously described in details (Blanc et al., 1998). The instrument part is composed of a pyrometer that allows the on-line temperature measurement of the sample at the upper surface and a precision balance that allows the follow-up of the sample and support set mean mass. The infrared panel is composed of 9 quartz lamps with a tungsten filament used in the wave length about 1.2 μm that allows densities ranging between 0 and 12 kW/m².

Modeling

The dynamic model of the painting film sample infrared drying is characterized by the temperature T and by the distributed humidity X on dry basis. The temperature is assumed to be lumped due the low thickness of the sample and due to the thermal characteristics of the support. This assumption has been experimentally checked. The PDE model S_{NL} is deduced from the following mass and energy balances.

Mass transfer

In the case of shrinking material, assuming a unidirectional transfer along the thickness z, the transfer of the solvent is diffusional and convective. In an eulerian (fixed) framework (z,t), this transfer is function of the solid deformation rate. By introducing a lagrangian (mobile) framework (ξ,t), this leads to write the diffusion equation of the solvent as follow (more details for the modelling and the parameter expressions may be found in (Blanc et al., 1997, Blanc et al., 1998)):

$$\frac{\partial X(\xi,t)}{\partial t} = \frac{\partial}{\partial \xi}\left(\frac{D(X,T)}{(1+\beta^* X)^2} \frac{\partial X}{\partial \xi} \right) \tag{1}$$

One has introduced the new independent space variables ξ to account for the shrinkage phenomena assumed to be characterized by a linear relation:

$$\frac{d\xi}{dz} = \frac{1}{1+\beta^* X} \tag{2}$$

The initial condition is, at t=0 and for $0 \le \xi \le \delta_{dry}$, $X(\xi,t) = X_i$. The two boundary conditions are:

- $\forall t > 0$ and at $\xi = 0$: $\dfrac{\partial X(\xi,t)}{\partial \xi} = 0$ (3)
- $\forall t > 0$ and at $\xi = \delta_{dry}$: $\dot{m}(\overline{X},T) = -\dfrac{D(X,T)\rho_{dry}}{(1+\beta^* X)^2} \dfrac{\partial X}{\partial \xi}$ (4)

where $\dot{m}(\overline{X},T)$, the drying rate is expressed by the film theory (Bird et al., 1960) and $\overline{X}(t)$ is the mean humidity on dry basis. As reported in the literature for polymeric solutions (Okazaki et al., 1974), it is assumed that the mass diffusion coefficient varies with the temperature and with the humidity content according to the relation:

$$D(X,T) = D_0 \exp(-\frac{Ea}{\tilde{RT}}) \exp(-\frac{a'}{X}) \quad (5)$$

(D_0 represents the pre-exponential factor, Ea is the activation energy and a' is the humidity parameter).

Heat transfer

Due to the small painting film thickness and due to the great thermal heat diffusivity of the iron support, the temperature of the whole system (painting film + support) is assumed to be uniform. Consequently and neglecting the heat due to the reaction, an overall heat balance accounting for the radiative and the convective heat losses and the evaporation losses (Figure 1)

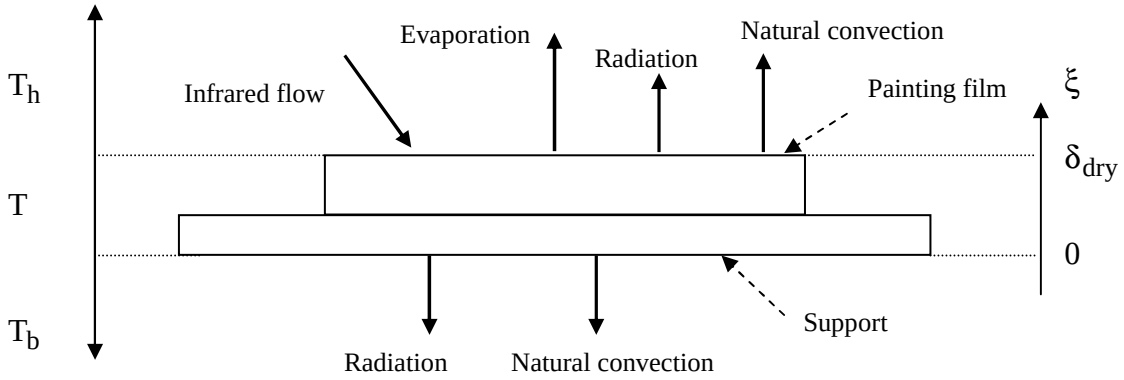

Figure 1: Thermal Flows.

leads to:

$$\left(\rho_p c_{pp} \delta_p + \rho_s c_{ps} \delta_s\right) \frac{dT}{dt} = \alpha_{ir}(\overline{X}) \dot{q} - h_c(T - T_h) - \sigma_h(T^4 - T_h^4) - h_c(T - T_b) - \alpha_s \sigma(T^4 - T_b^4) - l_v(T) \dot{m}(\overline{X}, T) \quad (6)$$

with the initial condition $T(t=0) = T_i$ and where the infrared flow $\dot{q}(t)$ is the manipulated variable.

OBSERVER DESIGN

Observer is a software sensor (algorithm) used to reduce the effects of noise of measurements as well as to estimate variables which are not measured. This tool originated from control science, and was initially developed for linear dynamic systems (Luenberger, 1966) and has been more recently extended to non-linear dynamic systems. If the model fulfils the so-called `observability' properties, the software sensor provides real-time estimates of the key process variables. The point of this theoretical device lies in the juxtaposition of the two types of information available on the system: its theoretical behaviour supported by the model, and its behaviour represented by the on-line measurements. The observers were first developed based on an ordinary differential equation model. In our work, we develop an observer based on the PDE model like in (Xu et al., 1995; Ligarius et al., 1998; Hua et al., 1998). Finally, based on the control $u(t) = \dot{q}(t)$ and on the measured process output $y_p(t) = T(t)$, the observer estimates the humidity profile $\hat{X}(z,t)$ in the sample.

PROCESS CONTROL STRATEGY

Model Predictive Control strategy

In a previous work (Dufour et al., 2003), we have introduced a MPC strategy to solve an output trajectory tracking problem based on a PDE model (Dufour et al., 2004). Here, the control problem can be stated in a more general framework: it is an on-line optimization problem over a receding horizon where the cost function J to be minimized reflects any control problem and where any constraints on measured output variables or estimated state variables may be explicitly specified. Since the problem is solved numerically, a mathematical discrete time formulation is given (more details for the parameter expressions may be found in (Dufour et al., 2003, Dufour et al., 2004)):

$$\begin{cases} \min_{\tilde{u}} J(\tilde{u}) = \sum_{j=k+N_i^0}^{j=k+N_f^0} g(y_{ref}(j), x_{ref}(j), y_p(j), \hat{x}_p(j), u(j-1)) \\ \tilde{u} = [u(k) = \dot{q}(k) ....u(j) = \dot{q}(j) ...u(k+N_c-1) = \dot{q}(k+N_c-1)] \\ \text{and } \forall j \in \{k+N_c, ..., k+N_f-1\} : u(j) = u(k+N_c-1) \\ \text{subject to constraints on the manipulated variable:} \\ u_{min}(j) \le u(j) \le u_{max}(j) \forall j \in \{k+1, k+N_f\} \\ \Delta u_{min}(j) \le u(j) - u(j-1) \le \Delta u_{max}(j) \forall j \in \{k+1, k+N_f\} \\ \text{subject to m constraints on the output and state variables:} \\ h^n(y_{ref}(j), x_{ref}(j), y_p(j), \hat{x}_p(j), u(j-1)) \le 0 \forall j \in \{k+N_i^n, k+N_f^n\}, n \in [1, m] \end{cases} \quad (7)$$

where k (resp. j) is the actual (resp. future) discrete time index, y_{ref} (resp. x_{ref}) describe the specified behaviour for the process measure y_p (resp. for the estimated process state $\hat{x}_p$). $\tilde{u}$ is the optimization argument. N_i^n (resp. N_f^n) are the initial (resp. final) horizon predictions, $N_f = \max_{n \in [0,m]} N_f^n$, N_c is the control horizon. In this formulation, it is first to notice that in the cost function expression, the knowledge of the process behaviour is required over the prediction horizon (i.e. for future times). These information are obviously not available at any present time k. This problem is overcome using, in an internal model control (IMC) structure (Bequette, 1998), an observer (Figure 2). In this structure, the manipulated variable is applied to both the process and its model. This structure allows reformulating the control problem since:

$$\begin{cases} y_{ref}(j) - y_p(j) = y_d(j) - y_m(j) = (y_{ref}(j) - e_y(j)) - y_m(j) \\ x_{ref}(j) - \hat{x}_p(j) = x_d(j) - x_m(j) = (x_{ref}(j) - \hat{e}_x(j)) - x_m(j) \end{cases} \quad (8)$$

Assumption: (Morari et al., 1983)

The error between the process output and the model output remains constant over the prediction horizon. The error value is updated at each sampled time *k* thanks to new measurements from the plant.

According to this assumption and with the IMC structure, the function g involved in the cost function can be expressed as $g(y_{ref}(j), x_{ref}(j), e_y(k), \hat{e}_x(k), y_m(j), x_m(j), u(j-1))$ and the constraints as $h^l(y_{ref}(j), x_{ref}(j), e_y(k), \hat{e}_x(k), y_m(j), x_m(j), u(j-1))$. This allows introducing the measures, the estimated measures, and the model into the control algorithm. From a practical point of view, the second problem is now to reduce the computational time needed to solve the constrained optimization problem during the sampling period. Indeed, the model aims at predicting the future dynamic behaviour of the

process over the finite prediction horizon and therefore has to be solved on-line. To reduce the resolution time required by the on-line nonlinear PDE model involved during the optimization task, we use a linearization method (Friedly, 1972) of the nonlinear model S_{NL} about a similar nonlinear model S_0 computed off-line by choosing its input u_0. Finally, the off-line solved nonlinear model S_0 and the on-line solved time-varying linearized model S_{TVL} replace the initial nonlinear model S_{NL} as depicted Figure 2 (Dufour et al., 2003). Such controller is efficient even if modelling errors may exist (Dufour et al., 2003).

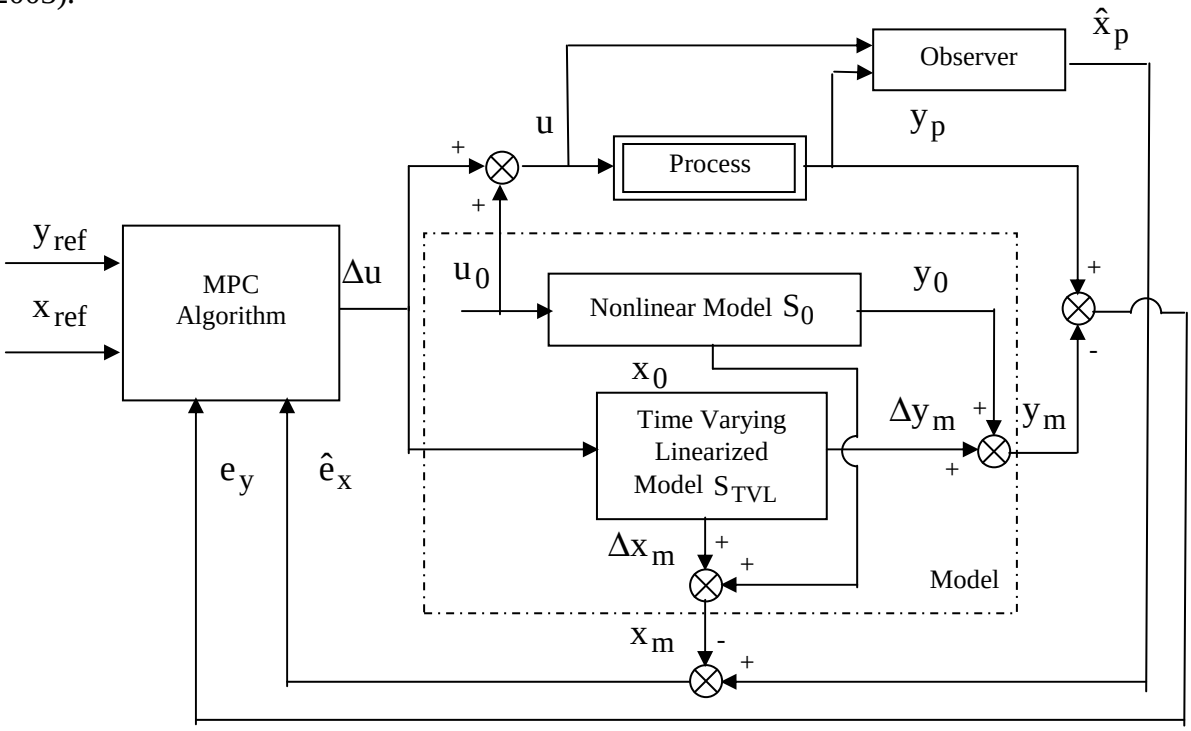

Figure 2: Observer based Time Varying Linearized Internal Model Control structure.

The control objective is now to find the variation Δu of the manipulated variable u about a chosen trajectory u_0 leading to the best optimization result. A constrained optimization problem including an on-line resolution of the linear model S_{LTV} has therefore to be solved (Dufour et al., 2003). Concerning input constraints, they are handled replacing the constrained sequence $\Delta\tilde{u}$ by an unconstrained sequence through a simple hyperbolic transformation (Fletcher, 1987, Dufour et al., 2003) that uses the constraints bounds. Output-state constraints are accounted for through an exterior penalty method (Fletcher, 1987). The optimizer argument is now an unconstrained argument and any unconstrained optimization algorithm can be used to solve the final on-line penalized optimization problem (Dufour et al., 2003): widely known and used for its robustness and convergence properties, we apply the Levenberg-Marquardt's algorithm (Fletcher, 1987), where the optimization argument is determined at each sample time k using the process measurement, the process state estimation (Xu et al., 1995) and the model prediction.

SIMULATION RESULTS

The optimization of the control of the process behaviour is dealing with the minimization of the processing time (hence, the minimization of the inverse of the drying rate) while accounting for any constraints. The state constraints are for the moment not specified. Therefore, to demonstrate the validity of the approach, the following constraints (on the input magnitude and on the input velocity) are specified:

$$\begin{cases} \mathrm{u}_{\min} = 0W.m^{-2} \le u(k) \le u_{\max} = 12kW.m^{-2} \\ \Delta u_{\min} = -500W.m^{-2} \le \mathrm{u(k)} - u(k-1) \le u_{\max} = 500W.m^{-2} \\ \mathrm{X}(\zeta_1, k) - \mathrm{X}(\zeta_2, k) \le X_{\max} = 0.014kg.kg^{-1} \end{cases} \quad (9)$$

whith the positions $\zeta_1 = 0.8 * \delta_{\mathrm{dry}}, \zeta_2 = 0.9 * \delta_{\mathrm{dry}}$. The sampling time is 1s and a correct tuning for the horizons is N_i^0=1, N_f^0=10. Simulation results show that a realistic infrared flow may be applied by the MPC (Figure 3 shows the magnitude constraints and Figure 4 shows the velocity constraints) in order to minimize the operating time. In the meantime, the specified state constraint is always satisfied (Figure 5): the state constraint satisfaction clearly limits the infrared flow applied (see the change of infrared flow dynamic from k=20s). This controlled drying cycle can be compared with another drying cycle where no constraints were specified for the difference of humidity between ζ_1 and ζ_2 (Figure 6). Therefore, MPC clearly allows maintaining the state constraint inside the specified envelope, while increasing the processing time as expected.

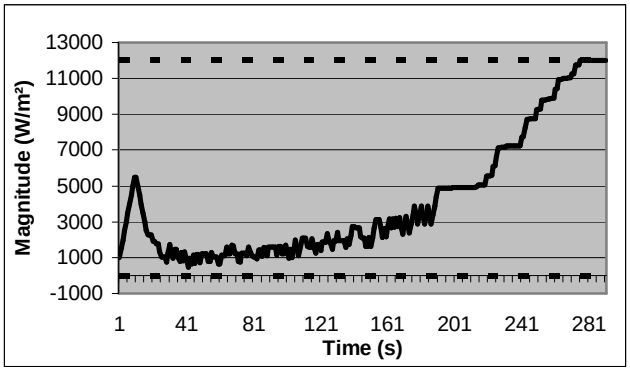

Figure 3: Constrained magnitude of the infrared flow

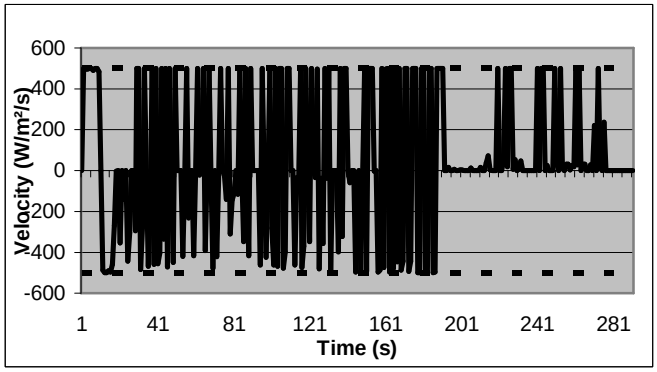

Figure 4: Constrained velocity of the infrared flow

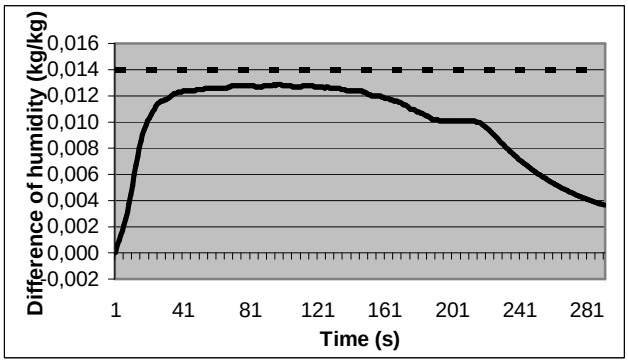

Figure 5: Constrained difference of humidity between ζ_2 and ζ_1

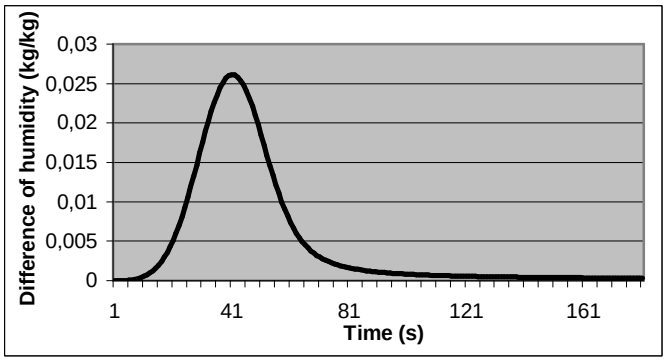

Figure 6: Unconstrained difference of humidity between ζ_2 and ζ_1

CONCLUSION

In this paper, an efficient approach for any constrained optimal control of an infrared drying process has been shown. A diffusional model is used leading to the knowledge of the drying dynamic characteristics, i.e. the temperature and mass content. To allow the on-line application, the nonlinear diffusional model is first solved off-line. Adjustments in the infrared flow to apply are then computed on-line using a linearized model involved in the constrained optimization problem. The MPC approach is based on an observer to estimate the unmeasured humidity profile. The next step is concerned with the experimental

validation of the approach and with the definition of the constraints that will really limit the processing time.

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