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RESERVED SPACE

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

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This paper deals with the model predictive control of an infrared drying process of a water based epoxy-amine painting. During the drying cycle, the control problem is to optimize the use of the process under constraints. This approach is based on a nonlinear dynamic unidirectional diffusional model of the infrared drying phenomena where both heat and mass transfers under shrinkage conditions are accounted for. To validate our approach, simulation results presented here deal with the minimization of the processing time while accounting for a constraint specified on a difference of humidity inside the sample.

Keywords: infrared drying process, observer based model predictive control, painting drying, heat and mass transfer.

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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 plaint sheets, cans, etc.). Optimal industrial use of an infrared dryer may lead to the minimization of any objective function while handling any quality constraints dealing with the drying characteristics (i.e. the temperature and the humidity profile). These constraints deal with the final product quality: bubbles and fissures phenomena that can happen during the polymerization reaction have to be avoided. Model Predictive Control (MPC) or receding horizon control refers to a class of control algorithms widely used in industrial applications in which a dynamic process model is used to optimize process performance (Qin and Badgwell 2003). 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 the use of a MPC strategy (Dufour et al. 2003) that allows here, for an infrared drying process of a water based epoxy-amine painting, to minimize the operating time while accounting for a constraint dealing with a difference of humidity inside the sample. Indeed, quality constraints are not known for the moment but they are probably based on the humidity gradient profile inside the sample since it is the inner driving force during the drying. Our approach was previously experimentally validated for the trajectory tracking of the measured temperature or the measured mean humidity (Dufour et al. 2004). In this paper, the unmeasured humidity profile is assumed to be estimated by 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 aspects are briefly discussed and the MPC strategy is reminded. Finally, simulation results are discussed.

Knowledge-based Modeling

Painting formulation and characteristics

Due to the great complexity of industrial paintings, the painting used here is a water based epoxy-amine painting formulated in our laboratory. This permits 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 phenomena is not 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 in dry basis initially). 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, Laurent and Andrieu 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 in 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 following PDE model 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 eurelian (fixed) framework (z,t), this transfer is function of the solid deformation rate. For the solvent, introducing a lagrangian (mobile) framework (ξ,t), the diffusion equation (more details may be found in (Blanc et al. 1997, Blanc Laurent and Andrieu 1998)) is:

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

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

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

The initial condition is, at t=0 and for $0 \le \xi \le \delta_{dry}$, $\mathrm{X}(\xi,t) = \mathrm{X}_i$.

The two boundary conditions are:

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

where $\dot{m}\left(\overline{\mathrm{X}},T\right)$, the drying velocity, is expressed by the film theory (Bird Stewart and Lighfoot 1960) and $\overline{\mathrm{X}}(t)$ is the mean humidity in 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:

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

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) leads to:

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

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

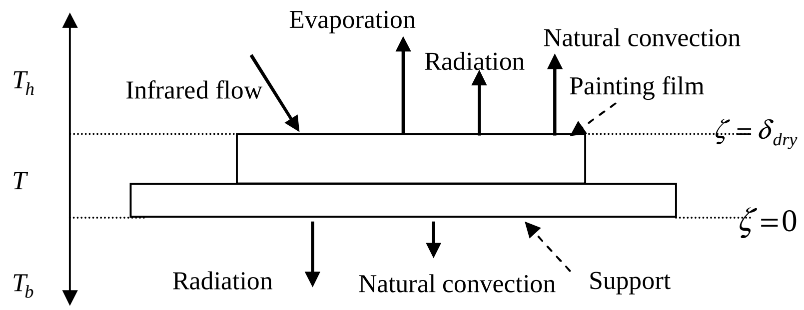

Figure 1: Thermal Flows.

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 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 real behaviour represented by the on-line measurements. The observers were first developed based on an ordinary differential equation model. In our work, we assumed that an observer based on the PDE model like in (Ligarius Gauthier and Xu 1998) is available. 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. The estimated process state is $\hat{x}_p(t) = (\hat{X}(z,t)\ \mathrm{T(t)})^T$.

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 is a general 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:

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

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, $N_f = \max_{n\in[0,m]} N_f^n$, and N_c is the control horizon. From a practical point of view, the problem is now to reduce the computational time needed to solve the constrained optimization problem during the sampling period. To reduce the resolution time required by the on-line nonlinear PDE model involved during the optimization task, we use a linearization method of the nonlinear model about a similar nonlinear model chosen and computed off-line (Friedly 1972). Finally, the off-line solved nonlinear model and the on-line solved time varying linearized model replace the initial nonlinear model (Dufour et al. 2003). The control objective is now to find, on-line, the variation of the manipulated variable about the trajectory chosen off-line leading to the best constrained optimization result (Dufour et al. 2003). Concerning the constrained argument $\tilde{u}$, it is replaced by an unconstrained argument $\tilde{p}$ through a simple hyperbolic transformation (Dufour et al. 2003) that uses the constraints bounds. Output and state variables constraints are accounted for through an exterior penalty method. The optimizer argument is finally an unconstrained argument and any unconstrained optimization algorithm can be used to solve this final on-line penalized optimization problem (Dufour et al. 2003): widely known and used for its robustness and convergence properties, the Levenberg-Marquardt's algorithm is used where the optimization argument is determined at each sample time k using the process measurement, the process state estimation and the model prediction.

Simulation Results

The following input constraints are specified:

$$\begin{cases} \mathrm{u}_{\min} = 0W.m^{-2} \le u(k) \le u_{\max} = 12kW.m^{-2} \\ \Delta u_{\min} = -500W.m^{-2}.\mathrm{s}^{-1} \le \mathrm{u(k)} - u(k-1) \le u_{\max} = 500W.m^{-2}.s^{-1} \end{cases} \quad (8)$$

whereas the following state constraint is accounted for (constrained case) or not accounted for (unconstrained case):

$$\mathrm{X}(\zeta_1 = 0.8 * \delta_{dry}, k) - \mathrm{X}(\zeta_2 = 0.9 * \delta_{dry}, k) \le X_{\max} = 0.014 kg.kg^{-1} \quad (9)$$

It allows comparing results obtained when the processing time is minimized with and without state constraints.
In the unconstrained case, the maximal infrared flow is always applied (Figure 2) and it is just constrained by (8): the infrared flow initially increases with the

maximum velocity and then saturates at the maximum magnitude. In the meantime, the difference of humidity reaches 0.026 kg/kg (Figure 3) and the operating time becomes 181s. In the constrained case, simulation results show that a realistic infrared flow may also be applied by the MPC (Figure 4). In the meantime, the specified state constraint (9) is always satisfied (Figure 5) and, as expected, it limits the optimization task since the operating time has increased in this case (291s).

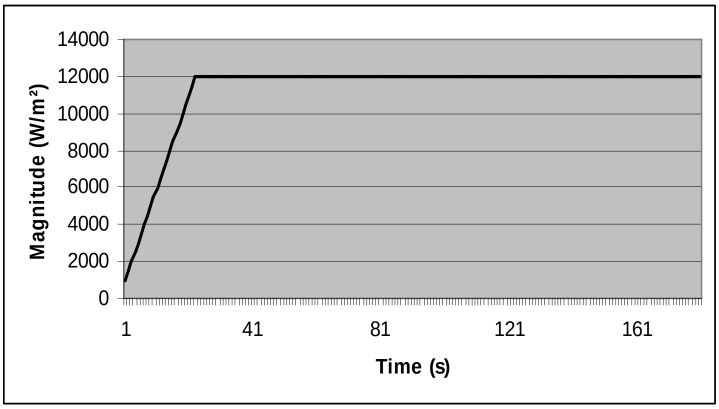

Figure 2: magnitude of the infrared flow (unconstrained)

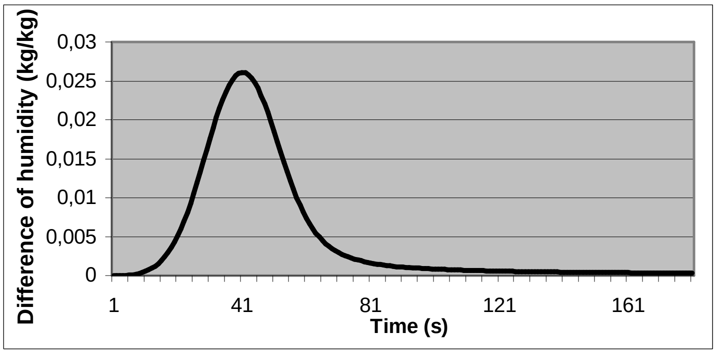

Figure 3: difference of humidity between ζ_2 and ζ_1 (unconstrained)

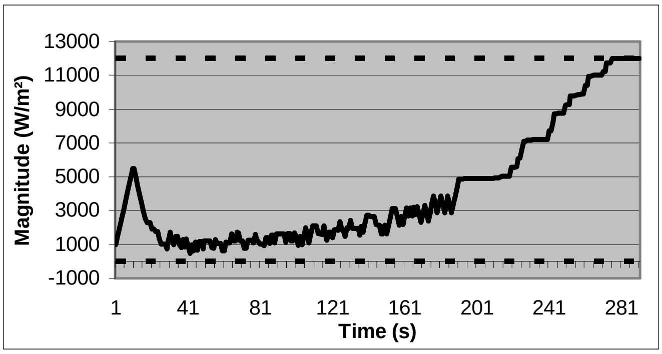

Figure 4: magnitude of the infrared flow (constrained)

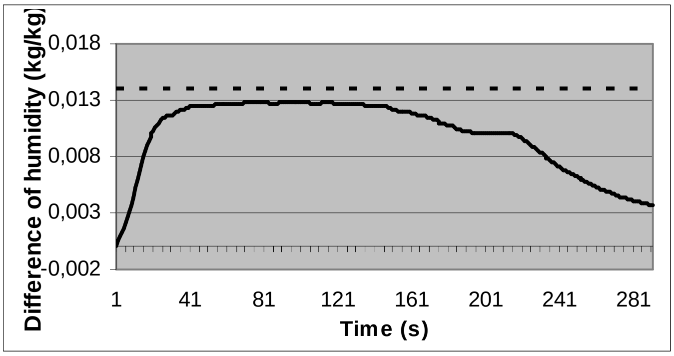

Figure 5: difference of humidity between ζ_2 and ζ_1 (constrained)

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 of this method, 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 the availability of an observer to estimate the unmeasured humidity profile.

The next step are concerned with the experimental validation of the observer based MPC and with the definition of the constraints that really limit the minimization of the processing time.

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