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Model Predictive Control of a Powder Coating Curing Process: an Application of the MPC@CB Software

Kamel Abid¹, Pascal Dufour¹, Isabelle Bombard¹, Pierre Laurent¹

1. Université de Lyon, Lyon, F-69003, France ; Université Lyon 1 ; CNRS UMR 5007 LAGEP (Laboratory of Process Control and Chemical Engineering), 43 bd du 11 novembre, 69100 Villeurbanne, France
E-mail: dufour@lagep.univ-lyon1.fr

Abstract: This paper deals with the control of a powder coating radiative curing process by infrared flow. It is based on a unidirectional dynamic modelling where both heat transfert and cure phenomena are accounted for within the thickness. The control problem is the constrained optimization of the curing cycle. This is solved using a special model predictive control framework: it is designed such that the calculation time is smaller than the sampling time (a few seconds), in spite of the need to solve the non-linear partial differential equation based model involved during the online constrained optimization task resolution. Simulation results show here the efficiency of the control software developed (MPC@CB) under Matlab. MPC@CB may be easily used for any other constrained control problem.

Key Words: Partial differential equations, Model predictive control, Control software, Powder coating curing, Heat transfer, Matlab.

1 INTRODUCTION

The present study, which is part of a research project [1], is concerned with the model based optimal control of the curing cycle of the powder. In this paper, the mathematical partial differential equation (PDE) model is first detailed: it is based on the knowledge of the fundamental mechanisms inside the powder during the infrared flow curing based on non-linear phenomena: the coupled thermal transfer and the curing. Then, the model predictive control approach is briefly detailed. In the last part, simulation results allow to compare PID and MPC performances.

2 FIRST PRINCIPLE MODEL AND CONTROL PROBLEM FORMULATION

Due to VOC regulations, powder coatings, as waterborne coatings, are replacing organic solvent based systems in coating techniques. They present numerous advantages, and yet they have not found the success they deserve and their applications domains remain unchanged: architecture (outdoor and indoor), furniture, domestic appliances, heaters, and cars accessories [1]. This is probably due to the fact that few global studies correlating curing kinetics, thermal modelling and optimization of the cure process have been made on the curing of powder coatings. This global approach is tackled here.

Powder coatings are finely ground plastic particles consisting of resin, cross-linker in thermosetting or thermoplastic powder coatings, pigments & extenders, and various flow additives and fillers to achieve specific properties. Quite recently, UV-curable coatings (the reaction is initiated by UV radiation) and low-temperature coatings designed for heat sensitive substrates have appeared on the coatings market. During the cure, powder coatings are present with a variety of morphologies [1]:

- at the powder state, they are applied on the steel panel by electrostatic means; the packing of the grains as well as

the thickness of the powder layer may be variable and each powder may present different particle size distributions;

- The curing begins with the melting of the powder coating (a viscous liquid); after viscosity decay due to the temperature, the polymerization reaction begins and the surface structure builds up until the end of the cure.

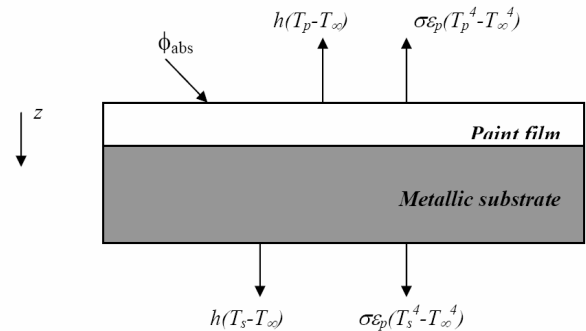


Fig 1. Schematic drawing of the “substrat+powder” sample.

The thermal model is based on the Fourier law of heat conduction and Figure 1 shows the boundary conditions applied at the top surface of the powder and at the bottom of the metallic substrate. The thermal balance uses both the temperature variable varying in the thickness of the powder coated metal sample, and the degree of cure conversion (which ranges from 0⁺ at the beginning to 1 at the end). Inside the powder, it leads to the following equation (the signification of the model parameters may be found in Table 1):

$$\frac{\partial T_p(z,t)}{\partial t} = \frac{\lambda_{c,p}}{\rho_p C_{pp}} \frac{\partial^2 T_p(z,t)}{\partial z^2} - \frac{e_p \Delta H_0}{C_{pp}} k_0 e^{\left(\frac{-E_a}{RT_p(z,t)}\right)} x^m (1-x)^n \quad \forall z \in]0, e_p[\quad \forall t > 0 \quad (1)$$

where T_p is the temperature across the powder film, which thickness is e_p .

The thermal balance inside the substrate leads to the following equation for the temperature T_s inside the substrate, which thickness is e_s :

$$\frac{\partial T_s(z,t)}{\partial t} = \frac{\lambda_{c,s}}{\rho_s C_{ps}} \frac{\partial^2 T_s(z,t)}{\partial z^2} \quad \forall z \in]e_p, e_p + e_s[\quad \forall t > 0 \quad (2)$$

The boundary conditions are:

$$\begin{aligned} -\lambda_p \frac{\partial T_p(z,t)}{\partial z} &= \alpha_{ir} \phi_{ir}(t) \dots \\ \dots - \sigma \varepsilon_p (T_p^4(z,t) - T_{ext}^4) \dots \\ \dots - h_p (T_p(z,t) - T_{ext}) &\text{ at } z = 0, \forall t > 0 \end{aligned} \quad (3)$$

where $\phi_{ir}(t)$ is the manipulated variable,

$$-\lambda_{c,p} \frac{\partial T_p(z,t)}{\partial z} = -\lambda_{c,s} \frac{\partial T_p(z,t)}{\partial z} \text{ at } z = e_p, \forall t > 0 \quad (4)$$

expresses the continuity of the thermal flow at the interface of the powder and the substrate, and:

$$\begin{aligned} -\lambda_s \frac{\partial T_s(z,t)}{\partial z} &= \dots \\ \dots - \sigma \varepsilon_s (T_s^4(z,t) - T_{ext}^4) \dots \\ \dots - h_s (T_s(z,t) - T_{ext}) &\text{ at } z = e_p + e_s, \forall t > 0 \end{aligned} \quad (5)$$

The initial condition is:

$$T_p(z,t) = T_s(z,t) = T_{ext} \quad \forall z \in [0, e_p + e_s], t = 0 \quad (6)$$

Concerning the degree of cure $x(z,t)$ of the powder, the polymerization reaction is characterized by the Sesták-Berggren law:

$$\frac{\partial x(z,t)}{\partial t} = k_0 e^{\frac{-E_a}{RT_p(z,t)}} x^m (1-x)^n \quad \forall z \in [0, e_p], \forall t > 0 \quad (7)$$

The initial condition is:

$$x(z,t) = 0 \quad \forall z \in [0, e_p], t = 0 \quad (8)$$

The thermo physical properties of the substrate have been found in the literature. The thermo physical properties of the paint were provided by our paint supplier. More details about the modelling may be found in [2].

Table1. Nomenclature

Cp	Heat capacity	J.kg ⁻¹ .K ⁻¹
e	thickness	m
Ea	Activation energy	J.mole ⁻¹
h	Convective exchange coefficient	W.m ⁻² .K ⁻¹
ΔH₀	total specific heat of the polymerization reaction	J.kg ⁻¹
k₀	Pre-exponentiel factor	s ⁻¹
m, n	Order of reaction	-
R	Universal gas constant	J.mol ⁻¹ .K ⁻¹
T	Temperature	K

x	Conversion degree	-
α	Absorption coefficient	-
ε	Emissivity	-
φ	Radiative flux	W.m ⁻²
λ_c	Thermal conductivity	W.m ⁻¹ .K ⁻¹
λ	Wavelength	μm
ρ	Density	kg.m ⁻³
σ	Stefan-Boltzmann constant	W.m ⁻² .K ⁻⁴
ir	infrared emitter	-
ext	exterior	-
p	Paint film	-
s	Metallic substrate	-

3 PROCESS CONTROL STRATEGY

In control theory, due to the complexity of the problem, relatively few studies are devoted to the control of processes explicitly characterized by a PDE model. Even if various methods are proposed to control such distributed parameter systems, there is no general framework yet. In order to implement, with a computer, a low order model based controller, the original PDE model is usually simplified into an ordinary differential equation (ODE) model. Such a finite dimensional approximation is based on the finite differences method, on the finite volume method, on the orthogonal collocation method, or on the Galerkin's method. Other works use properties of the initial PDE system before finite dimension controller synthesis: recently, Christofides developed order reduction by partitioning the eigen-spectrum of the operator of the PDE system [3] and methods based on approximate inertial manifold for spatial discretization of the PDE [4]. Other works for controller synthesis of nonlinear PDE systems are based on symmetry groups, infinitesimal generators and invariant conditions [5]. Concerning [6], finite dimensional controllers are obtained through model reduction based on various methods: singular value decomposition, Karhunen-Loève expansion or eigen-function method. With this method, an interesting framework is provided with proof of closed-loop stability for the quadratic dynamic matrix control (QDMC) of a PDE system [7]. In [8], stability conditions for closed-loop control of linear PDE with finite dimensional controller are given in time domain and frequency domain through semi-group analysis. In [9], based on semi-group theory, proofs were given for the closed-loop stability of PI control for a linear PDE system.

The control strategy we use here is the model-based predictive control (MBPC), also named model predictive control (MPC), or receding horizon control (RHC). It is a particular class of optimal controller [10]. It consists in solving an explicit optimization problem formulated into the future. The main advantage is that constraints (such as manipulated variables physical limitations, constraints due to operating procedures or safety reasons...) may be explicitly specified into this formulation. In this structure,

a model aims to predict the future behavior of the process and the best one is chosen by a correct tuning of the manipulated variables. This procedure is repeated at each sampling time with the update on the process measurements. Since its first development at the early 70's, many concepts have appeared (DMC, QDMC, GPC ...) and after the PID, it has become the second control paradigm in the history of control. Thousands of industrial applications of MPC exist today, for example in the chemical and petrochemical industries.

In previous real applications [11, 12], it has been shown how a special PDE model MPC framework [11] may be used for the control of such PDE system, in spite of the relatively large size and non-linearity of the model state computed during the optimization. This controller is designed such that the calculation time is smaller than the small sampling time (a few seconds). This controller is built as a compromise between the small calculation time allowed, and the accuracy of the model used in the on-line model based optimization problem to solve. It has been shown how this MPC framework is robust with respect to modelling errors and uncertainties. Moreover, unfeasibility of the output constraint is also handled, such that the less worst solution is found. Based on this framework, the control problem is a general optimization problem over a receding horizon N_p where the cost function J_{tot} to be minimized reflects any control problem J (trajectory tracking, processing time minimization, energy consumption minimization, ...) , and where any modeled constraints on measured or estimated output may be explicitly specified by J_{ext} . Since the problem is solved numerically, a mathematical discrete time formulation is given [11]:

$$\min_p J_{tot}(p) = J(p) + J_{ext}(p) \quad (9)$$

where:

$$J_{tot}(p) = \sum_{j=k+1}^{j=k+N_p} h(y_{ref}(j), y_p(k), y_m(j), u(p(j))) \quad (10)$$

where k (resp. j) is the actual (resp. future) discrete time index, y_{ref} describe the specified constrained behavior for the process measure y_p , y_m is the continuous model output in the future. The unconstrained optimization argument is p : it is obtained from a simple hyperbolic transformation of the magnitude and velocity constraints specified for the manipulated variable u [11]. The optimizer argument is finally an unconstrained argument and any unconstrained optimization algorithm may be used to solve this on-line penalized optimization problem: 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 or estimation, the model prediction and the cost function J_{tot}

From a practical point of view, the next step in the problem formulation is to reduce the computational time needed to solve the unconstrained optimization problem during the

sampling period. We use a linearization method of the nonlinear PDE model about a similar nonlinear PDE model chosen and computed off-line. Finally, the off-line solved nonlinear PDE model and the on-line solved time varying linearized PDE model replace the nonlinear model [11].

4 CONTROL SOFTWARE: MAIN FEATURES OF MPC@CB¹

The codes of the MPC@CB software have been written with Matlab. It allows to realize the MPC under constraints of a continuous process. The originality of these codes is first the ease of their use for any continuous SISO process (Single Input Single Output), through the user files (where model equations have to be specified), synchronized by few main standards files (where the user has to make few (or no) changes). The model has to be given under the form:

$$\begin{cases} \dot{s} = f(s, u) \\ y = g(s) \end{cases} \quad (11)$$

i.e., there are any number of states variable s in this SISO model, it may be linear or not linear, time variant or time invariant, based on ODE and/or PDE.

Another original feature of the software is the straightforward resolution of various model based control problems through different choices:

- Open or closed loop control.
- MPC for a trajectory tracking problem, with or without the output constraint. The user may specify any reference trajectory.
- MPC to solve an operating time minimization problem, with or without the output constraint.
- In order to study the robustness of the control law, it is easy to introduce, for any model parameter, different values in the model (used in the controller) and in the simulated process. It is assumed that the simulated process and the model are described by the same equations.
- Closed loop control with PID in order to compare control performances with the MPC.
- Possibility to introduce a cascaded process (which input is the output controlled by the software)
- Possibility to specify any condition to stop the run before the final time.

The other originality is the method used to develop the codes: it is very easy to introduce new parts in the code, such as:

- MPC with a user defined problem.
- Handle SIMO, MISO or MIMO model (currently under development for another process).

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- Introduce a software sensor (observer) (currently under development for this process).
- Apply the software for a real time application (currently under development for this process).

5 SIMULATION RESULTS

The simulations presented here allow to compare the overall performances of the MPC scheme with respect to the performances of a PID. The manipulated variable is the infrared flow $\phi_{ir}(t)$. The output is the temperature at the bottom of the metallic substrate and it is measured. For the PID, a regulation problem is specified whereas for the MPC, a constrained optimization problem is stated: the constant set-point specified for the PID has to be reached as fast as possible, but it is not allowed to exceed this set-point at any time. Moreover, nonlinear velocity and magnitude saturation functions are added at the PID output to satisfy the manipulated variable constraints (which are naturally accounted for by the MPC). The simulation stops when each degree of cure is more than 99.9%.

5.1 Trajectory tracking without model uncertainties

In this simulation, the ideal case is assumed: the model perfectly matches the simulated process (same equations and same parameter sets). For a reference of 453.15K, Figures 2 shows that the regulation is effective, but that the MPC allows to end ending the cure faster than the PID. Indeed, during the first 50s, the optimal behavior spend 10 more seconds at the maximum infrared flow magnitude allowed (Figure 3): this leads to a difference of temperature of 15K at 50s and the temperature is almost at steady state at 70s with MPC, but at 130s with the PID. Since the degree of cure dynamic increases when the powder painting temperature increases (see (7)), the polymerization reaction is faster for MPC than PID (see Table 2): the curing time obtained with PID is 110% of the time needed by the MPC. In the meantime, even if it was not specified inside the optimizer, due the difference of curing time, less energy is needed during the cure by the MPC than the PID (see Table 2): the energy needed to end the cure of the thermoset painting powder with PID control represents 104% of the energy needed by the MPC. The overall performances are therefore better with MPC than PID. Another simulation based on the reference of 423.15K leads to the same kind of conclusion.

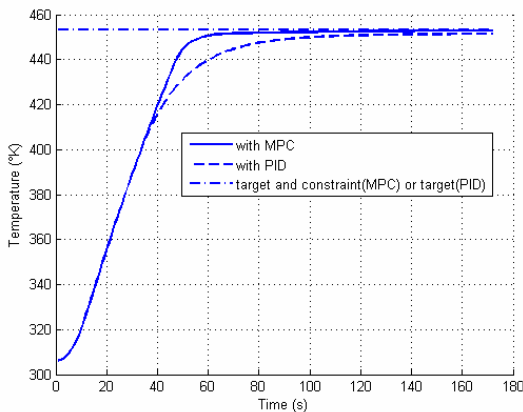


Fig 2. Output temperature with: (solid) Optimization by MPC of the dynamic of the output temperature, with output constraint, constrained target is 453.15K; (dash) PID control, based on the tracking of the temperature reference, reference is 453.15K

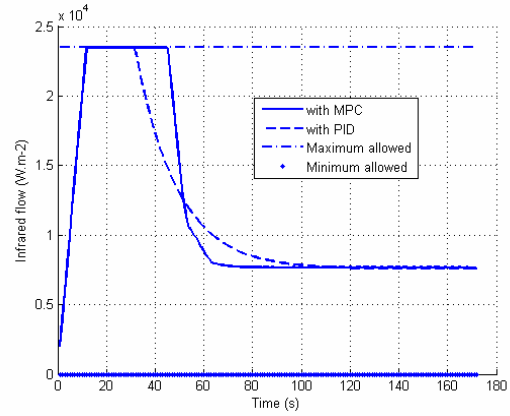


Fig 3. Infrared flow magnitude with: (solid) Optimization by MPC of the dynamic of the output temperature, with output constraint, constrained target is 453.15K; (dash) PID control, based on the tracking of the temperature reference, reference is 453.15K

Table 2. Comparison of MPC and PID performances, with no modelling errors, and when the reference is 453.15K

Controller	MPC	PID
Curing time (s)	172 (100%)	190 (110%)
Energy consumption during the cycle (J/m ²)	1977554 (100%)	2065366 (104%)

5.2 Trajectory tracking with model uncertainties

In this simulation, the ideal case is no more assumed: the model used by the MPC and the simulated process have the same equations structure, but parameter uncertainties have been introduced:

- $\epsilon_s(\text{simulated process})=1.3*\epsilon_s(\text{model})$: the heat exchange with the exterior is less important in the simulated process than in the model,
- $\alpha_{ir}(\text{simulated process})=0.7*\alpha_{ir}(\text{model})$: less infrared flow is absorbed in the simulated model than in the model.

MPC gives here also better performances than PID (Figures 4 and 5). But the difference between each performance has increased: the curing time obtained with PID is now 115% (110% in the ideal case) of the time needed by the MPC, whereas the energy needed to end the cure of the thermoset painting powder by PID control represents 107% (104% in the ideal case) of the energy needed by MPC.

6 CONCLUSION

The curing time is longer for PID than MPC (from 7% to 15%), and PID requires the use of more infrared energy than MPC (from 4% to 7%): MPC therefore allows to spare both processing time and energy, and as a consequence money. Moreover, MPC guaranties that the

control action is physically applicable, and that the output constraint is satisfied (if a solution exists!), which is not the case for the PID. The performances obtained with the MPC are also less sensitive with respect to modelling errors than they are with PID. A model-based control software, MPC@CB, has been developed, and may be easily used for any other process.

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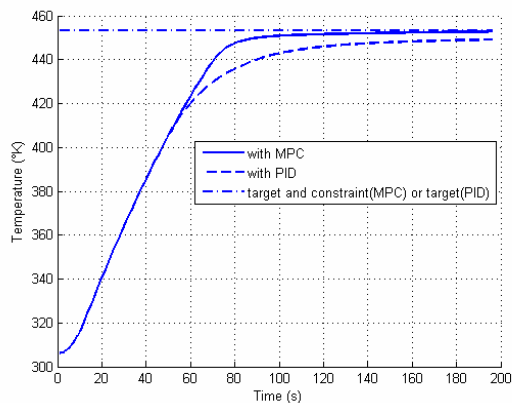


Fig 4. Output temperature, with parameter model uncertainties, with: (solid) Optimization by MPC of the dynamic of the output temperature, with output constraint, constrained target is 453.15K; (dash) PID control, based on the tracking of the temperature reference, reference is 453.15K

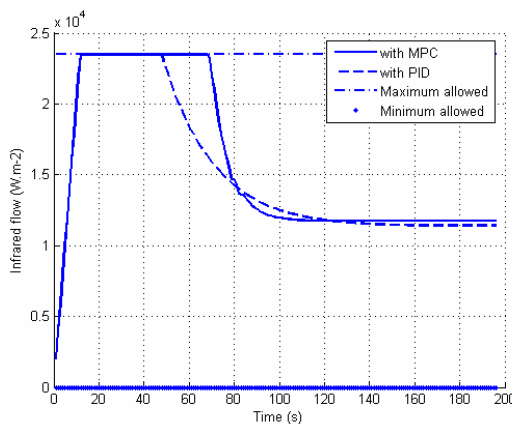


Fig 5. Infrared flow magnitude, with parameter model uncertainties, with: (solid) Optimization by MPC of the dynamic of the output temperature, with output constraint, constrained target is 453.15K; (dash) PID control, based on the tracking of the temperature reference, reference is 453.15K