NONLINEAR MODEL PREDICTIVE CONTROL OF UV-INDUCED THICK COMPOSITE MANUFACTURING PROCESS

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Abstract

In this paper the nonlinear model predictive control (NMPC) of UV-induced curing of composite material for manufacturing of thick parts is proposed. The process involves layer-by-layer curing of thin composite laminates to form thick part. The model for NMPC switches when a new layer is added to the existing layer. The layer addition times are determined externally. The offline optimal control is used to determine the optimal time and temperature profile which will give uniform cure distribution of a thick composite material. Once the temperature trajectory and optimal time sequences are found, the NMPC is implemented for online control. The objective is to determine theoretical optimal behavior (assuming the process measurement is available) which will be used for online switching NMPC for tracking the reference temperature.

Keywords: NMPC, Switching Systems, UV Curing, Additive Manufacturing, Optimal time control.

Introduction

Lightweight materials have a great potential for improving vehicle performance, it can improve the passenger vehicle fuel efficiency six to eight percent for each ten percent reduction in weight [1]. Fiber reinforced polymer composites are one of the most promising weight reduction technologies available today [1]. The manufacturing process of these composites are mainly thermal based curing process. However, recently radiation based curing process have shown a great potential for thick composites manufacturing. As discussed in the previous sections UV has limited penetration, this challenge has limited the application of UV to thin polymer films in applications such as printing inks and adhesives, printing plates, microcircuits and production of thin composite parts [2].

To overcome the cure depth limitation, a layer-by-layer deposition was recently introduced and have been implemented for production of thick composite parts manufacturing using UV as radiation source and acrylate matrix [3] and epoxy matrix [4-6]. This was then extended for a concurrent curing and layering approach where distinct process optimization opportunities were identified by examining the interplay between the underlying curing kinetics and UV attenuation [3-6].

All the recent proposed approaches focused on the offline optimal time control for determining the optimal input and/or layering time with the objective of uniform final cure distribution across the finished product. However, these approaches assume a uniform UV intensity in optimizing the layering time and hence the optimal layering times are optimal for the given input only. In this paper, we propose a model predictive control strategy for online control of UV-induced curing process.

Model predictive control (MPC) also referred to as receding or moving horizon control has been widely used in industry as an effective approach to deal with large multi-variable constrained control problems. It is a well-established control strategy in the chemical process industry which are typically characterized by a longer sampling periods. In recent years, however, the improvement in the processor speed and the development of new algorithms has extended the application of MPC to other applications such as automotive [7, 8, 9], aerospace [10, 11, 12] where typical sampling is in the order of milliseconds [13, 14, 15, 16]. The main advantage of MPC controller as compared to traditional proportional, integral and derivative (PID) is that it allows taking constraints on states, inputs and outputs of the system. Moreover, multivariable feedback control can be designed with similar procedural complexity as of single variable ones [13].

There are few papers where MPC has been applied for distributed parameter systems such as curing process of thick composites [17-19]. In these works, distribute parameter systems with high order dimension models are considered. However, the dimension of states is constant i.e. there is no change in dimension throughout the process. In our study we discuss on the distributed parameter NMPC which is highly nonlinear UV-induced curing of composites with UV intensity as a control input and process temperature and degree of cure considered as state.

The rest of the paper is organized as follows: Section II discusses the UV curing process model, Section III explain how the offline optimal time control is done. Section IV discusses the nonlinear model predictive control. The results and conclusions are included in Section VI.

Curing process model

Considering the 1D curing set up shown in Fig. 1 below, a single layer of material is exposed to a uniform UV source at the top.

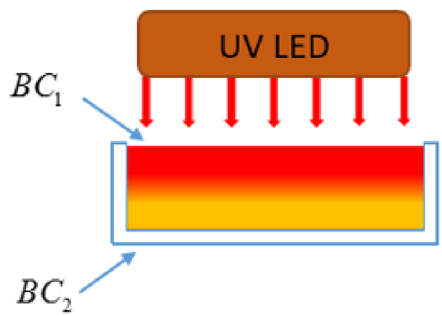

Figure 1. Schematic of UV-induced curing process

The curing process involves heat generation from polymerization (exothermic reaction), convection heat transfers at the top surface and conduction within the layer. These also need to be captured along with boundary conditions. The convective boundary condition (BC1) at the top and insulation boundary condition (BC2) at the bottom. The UV gets attenuated as it passes through the material and the intensity across the depth is given by Beer-Lamberts law [20- 22].

The temperature within the fiber-reinforced composites can be calculated using the law of conservation of energy together with a model for cure kinetics. By neglecting the energy transfer by convention, the energy conservation equation can be described as:

$$\rho c_p \frac{\partial T(y,t)}{\partial t} = k_z \frac{\partial^2 T(y,t)}{\partial y^2} + \rho_r \Delta H_r \frac{d\alpha(y,t)}{dt} \qquad [1]$$

where ρ and ρ_r are density of the composites and resin respectively, c_p is the specific heat capacity of composites, ΔH_r is the enthalpy of polymerization of the resin, k_y is the thermal conductivity in the direction perpendicular to the plane of the composite $T(y,t)$ is the temperature at time t and depth y, $\alpha(y,t)$ is the degree of cure of the resin at depth y and time t.

Equation (1) is coupled with the exothermic reaction (cure) rate equation of the unsaturated polyester resin which is given in Eq. (2).

$$\frac{d\alpha(y,t)}{dt} = \varphi S^q I_0^p \exp(-\lambda_c y)\, exp\left(\frac{-E}{RT_{abs}(y,t)}\right) \alpha^m(y,t)\big(1-\alpha(y,t)\big)^n \qquad [2]$$

where, φ is pre-exponential rate constant S is photo-initiator concentration, λ_c UV attenuation constant, E is activation energy, R is gas constant. [3] .

The convection and insulation boundary conditions (BC1 and BC2) are given in Eq. (3) and Eq. (4) respectively.

$$-k_z \frac{\partial T(y,t)}{\partial y} + \vartheta I_0 = h(T(y,t) - T_\infty) \quad [3]$$

$$\frac{\partial T(y_{max},t)}{\partial y} = 0 \quad [4]$$

where, y_{max} is the thickness of the fiber-reinforced resin.

The cure process model is then summarized as follows [23]:

$$\rho c \frac{\partial T(t,y)}{\partial t} = k_y \frac{\partial^2 T(t,y)}{\partial y^2} + \rho_r \Delta H_r \frac{d\alpha(t,y)}{dt} \quad [5]$$

$$-k_y \frac{\partial T(t,y)}{\partial y} + \vartheta I_0 = h(T(t,y) - T_\infty) \quad [6]$$

$$\frac{\partial T(t,l)}{\partial y} = 0 \quad [7]$$

$$\frac{d\alpha(y,t)}{dt} = \varphi S^q I_0^p \exp(-\lambda_c y)\, exp\left(\frac{-E}{RT_{abs}(y,t)}\right) \alpha^m(y,t)\left(1-\alpha(y,t)\right)^n \quad [8]$$

where ρ and c are the density and specific heat capacity of the epoxy, respectively; k_y is the thermal conductivity of the epoxy across the depth; $T(t,y)$ is the temperature at time t and depth y. ΔH is enthalpy of polymerization; $\alpha(t,y)$ is degree of cure at time t and depth y ; l is the thickness (depth) of the sample; A is pre-exponential constant; E is the activation energy ; R is universal gas constant; T_{abs} the absolute temperature in Kelvin; I_0 is the initial UV intensity; λ is UV attenuation constant.

Offline optimal control

In this section we pose an optimal control problem for the model described in Eqn. (5)-(8) to find the optimal layering time which will be used as a reference for NMPC.
We start by setting up a general cost function is the sum of integral cost, switching cost and terminal cost:

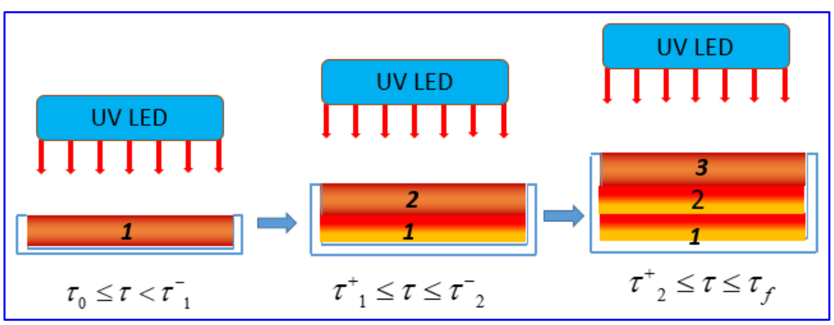

Figure 2: Schematic of layer-by-layer curing process

The temperature profiles for each layer is shown in Fig.3 and the final degree of cure is shown in Fig.4 and one can see that using the optimal curing times resulted in a minimal final cure deviation (<1 %). These results are used for online simulation which will be discussed in the following section.

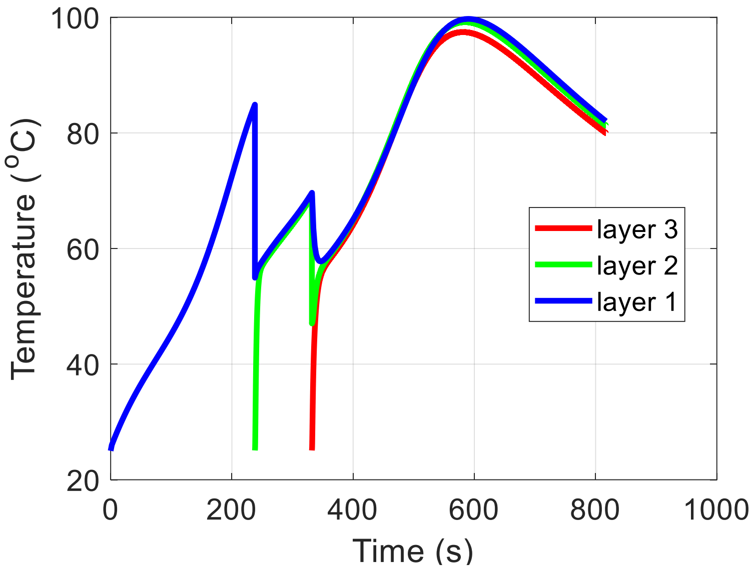

Figure 3: Temperature profile of three layers

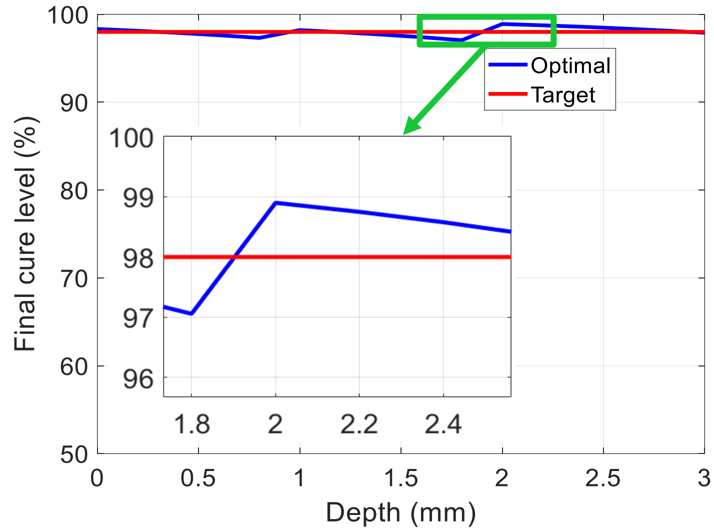

Figure 4: Final cure level of three layers

Nonlinear model predictive control

Model predictive control refers to a class of control algorithm in which a dynamic process model is used to predict and optimize process performance. The idea is to solve, at each sample time, an open-loop optimization in order to find the value of the manipulated variable is reiterated at the next sample time with the update of the process measurement. Today, MPC has become a control strategy widely used in industry. Indeed, MPC is well suited for high performance control since constraints can be explicitly incorporated into the formulation of the control problem [24]. In this section the Nonlinear MPC for tracking is of temperature profile is proposed.

Thermal based curing of composites have to follow a specific temperature profile (called cure cycle) to achieve a required quality of final product. Hence, researchers have been using temperature as a reference to control the curing process [25, 27,28]. In radiation based curing such as UV the initiation comes mainly from the photo-imitators which absorbs light. However, the propagation strongly dependent on temperature. As discussed in the previous section the optimal switching times, chosen with the objective of minimizing final cure deviation, resulted in near uniform final temperature. Therefore, for the NMPC the offline temperature profile which is found from offline optimal control with the objective of uniform cure distribution is used. The control problem considered here is the tracking of a reference temperature (Tref) and minimizing the control effort. The NMPC technique solves the optimal control problems repeatedly from the current measured state by online computation. After giving the initial control input u(t) and states x(t); the current control input at time t is found by determining the optimal control solution online over the interval [t, t+T p] with the objective of minimizing the temperature difference from a given reference and control input. As depicted in Fig. 5 the system involves mode change. The mode change times are as discussed earlier determined from offline optimal control with the objective of minimizing final degree of cure deviation across layers. In SNMPC the horizon may range from one mode to the next higher mode. In that case, the number of states increase and hence the cost function before and after the switching instant within that horizon is different. The ideal cost function should switch at the switching time. However, it may pose computational challenge. To reduce the computational burden, it is customary to use a reasonably reduced order for MPC. For this paper we used the same reduced order model (lower number of nodes) for NMPC simulation. (see Fig. 6).

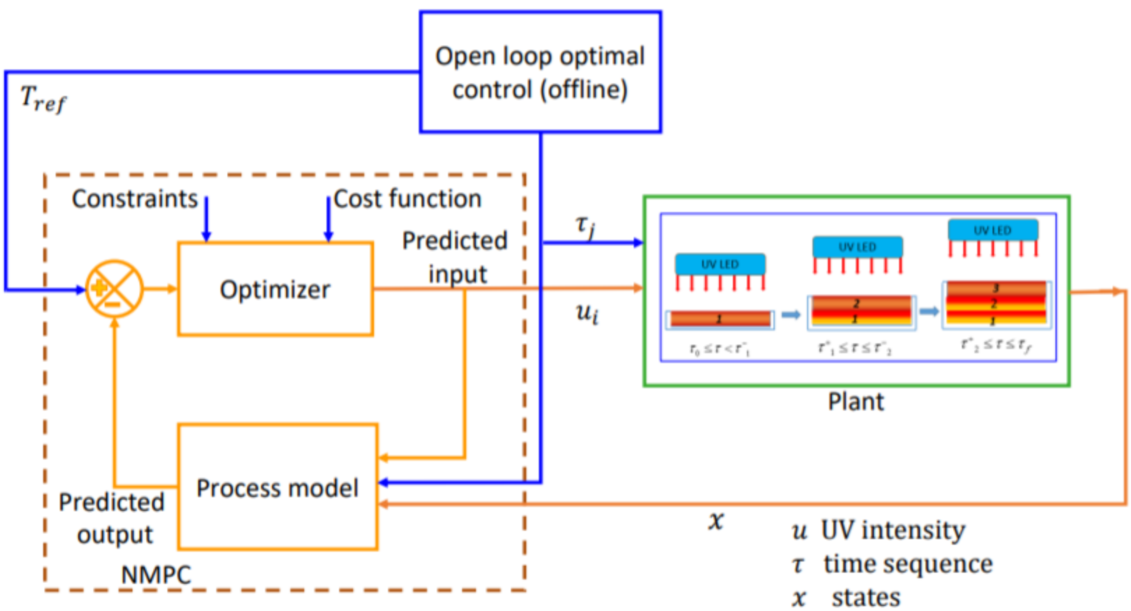

Figure 5. NMPC layout for layer-by-layer curing process

NMPC problem formulation with switching cost

The NMPC techniques solves the optimal control problems repeatedly from the current measured state by online computation. After giving the initial control input u (t) and states x (t); the current control input at time t is found by determining the optimal control solution online over the interval [t, t+Np] with the objective of minimizing the temperature difference from a given reference and control input. The objective function is given by Eq. (9):

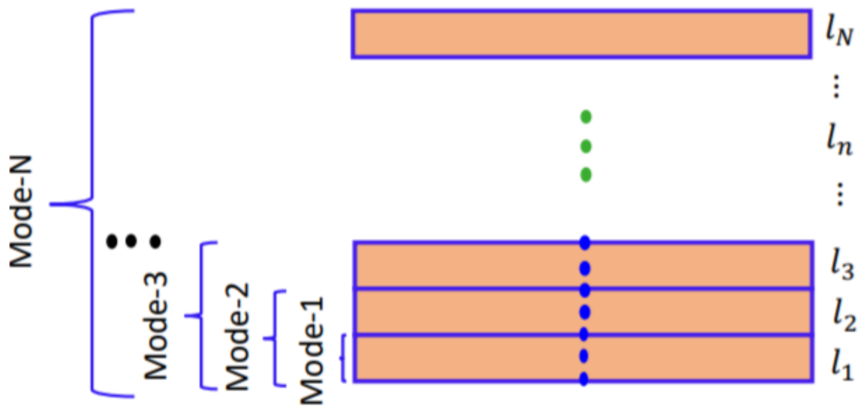

Figure 6. Reduced model for MPC

$$J_S = Q\left\{\sum_{k=1}^{N_s}\sum_{i=1}^{N_z(l_n)}(T(k,i)-r(k,i))^2 + \sum_{k=N_s}^{N_p}\sum_{i=N_z(l_n)}^{N_z(l_{n+1})}(T(k,i)-r(k,i))^2\right\} + R\sum_{k=1}^{N_p}u(k)^2 \qquad [9]$$

$$\text{S.t}\begin{cases} x_{k+1} = f(x_k, u_k) \\ u_{\min} \le u \le u_{\max} \\ x(0) = x_0 \end{cases}$$

where f is as given in in Eqns (5-9), Np is the prediction horizon (number of predictions), Mp ≤ Np is the control horizon , in this study the control horizon taken to be the prediction horizon (i.e Mp = Np), T is the temperature from SNMPC and r = Tref is reference temperature from the open loop offline optimal control , Q is the weighting matrix for predicted errors (Q ≥ 0) and R is the weighting matrix for control moves (R ≥ 0). Nz is the number of nodes in the given mode which is defined as described in Fig. 6. Herein, ln is the number of layers in mode N. For NMPC model the number of nodes considered are three therefore, the total number of nodes in mode n is: Nz = 3ln.

NMPC algorithm for switching system

The algorithm used for simulation of the SNMPC is as follows:

1. Calculate the switching instants (from offline open loop optimal control as described in the previous section)
2. At the k-th sampling instant, the values of the manipulated variables, u, at the next M sampling instants, {u(k), u(k+1), …, u(k+NP -1)} are calculated.
3. The set of NP control inputs is calculated to minimize the deviations from the reference temperature over the next NP sampling instants while satisfying the constraints.
4. When the sampling instant is equal to the switching time (new layer addition) the cost function switches from tracking temperature of the existing layers to tracking existing layers and the new layer (the size of the states being tracked increased). From this time to next switching instant the dimension of the states used in the objective function and constraints will be constant.
5. Then the first "control move", u(k), is implemented.
6. At the next sampling instant, k+1, the P-step control policy is re-calculated for the next P sampling instants, k+1 to k+NP, and implement the first control move, u(k+1).
7. Steps 2 and 6 are repeated for subsequent sampling instants.

Results and discussion

To demonstrate the effectiveness of the proposed SNMPC approach, three layer fiber-reinforced composite is considered. A prediction horizon of 100s and 10 steps is taken. Following the algorithms given above. Figures 7 to 9 show the reference temperature tracking and the corresponding control effort of bottom layer, middle layer and top layer respectively.

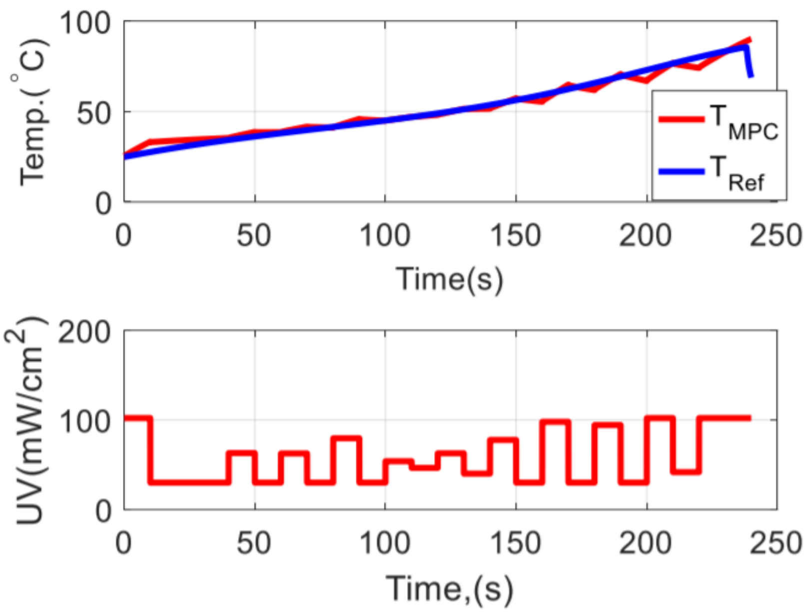

Figure 7 Layer 1 temperature tracking and control input

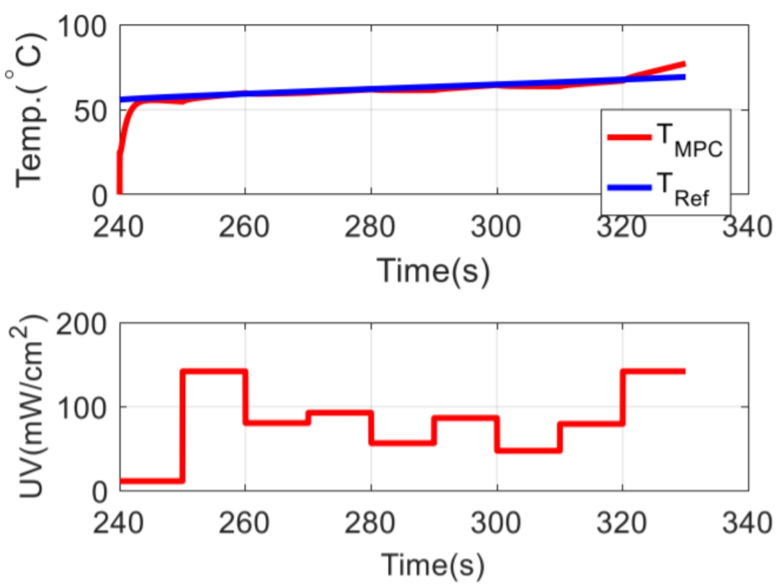

Figure 8 Layer 2 temperature tracking and control input

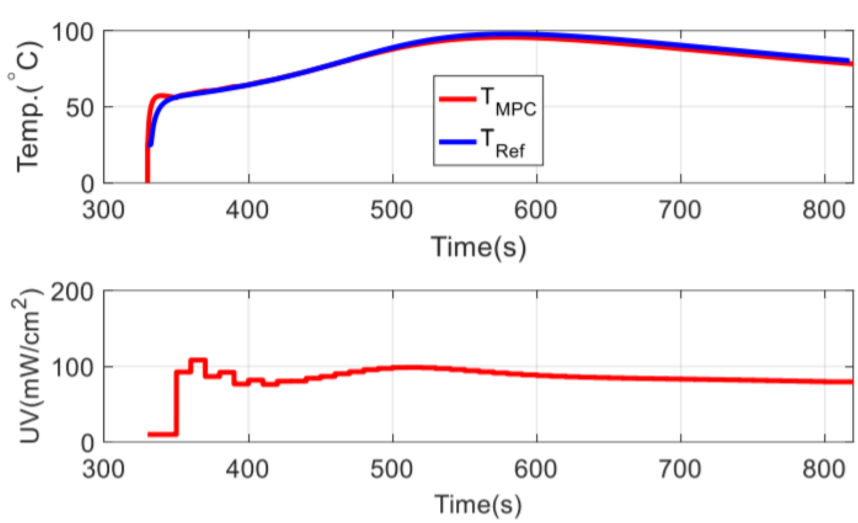

Figure 9 Layer 3 temperature tracking and control input

Figure 10 depicts the bottom layer reference temperature and the results of SNMPC for all layers. As can be seen in the figure, there is a very good agreement of the reference temperature and the SNMPC temperatures. To avoid confusion, the temperatures from SNMPC of all layers are compared with the bottom reference temperature. The deviation seen close to the end is mainly from the spatial difference of the layers and same deviation is observed on the offline result shown in Fig. 3.

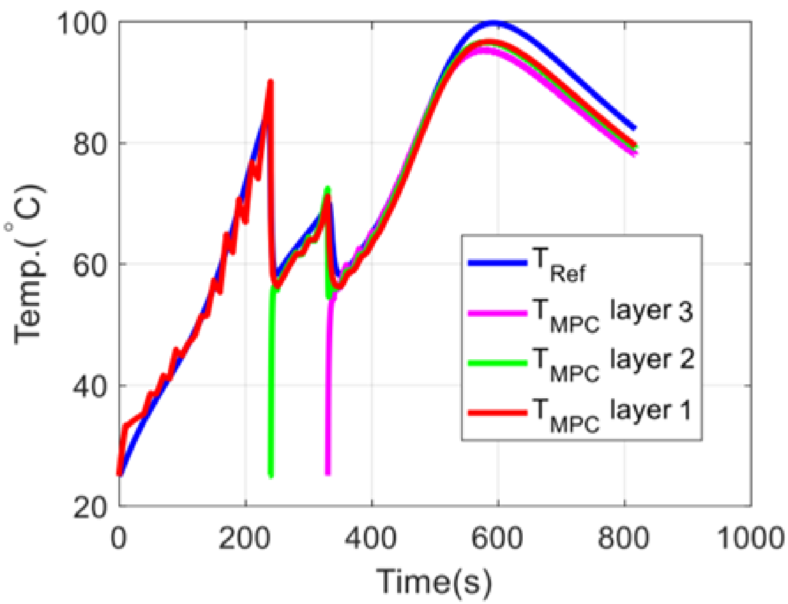

Figure 10 Comparison of three layers SNMPC temperatures with bottom layer reference temperature.

Conclusion

In this paper, online control method with NMPC is proposed for layer-by-layer curing of fiber reinforced composite. A nonlinear model predictive control (NMPC) scheme is outlined for UV-induced acrylate-based curing of a switching nonlinear model predictive control (SNMPC) for layer-by-layer curing process. The key characteristic is that the processes model switches when a new layer is added to the existing layer. Open loop optimal control is used to determine the optimal layering time and temperature profile which give a nearly uniform cure distribution of a thick composite material. Once the temperature trajectory and optimal time sequences are found, the SNMPC is implemented for online control. The objective is to determine theoretical optimal behavior which are then used for online SNMPC for tracking the reference temperature distribution. To demonstrate the effectiveness of the proposed approach a three-layer fiber-reinforced resin with two cases are considered and results show a very good agreement between the reference temperature distribution and SNMPC.

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