Hybrid Spectral/Neural Model Based Integrated Control and Supervision of a Distributed Thermal Process in IC Packaging

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Abstract—**It is difficult to achieve optimal curing for die attachment in IC packaging due to the lack of tools for on-line measurement. In practice, the cure schedule is typically determined in a trial and error process even though it is costly and may not guarantee the reliability of the adhesive die attach. A novel spectral model based integration of cure schedule optimization, supervision and decoupling control is introduced to maintain both reliability and throughput. The method is straightforward and effective, and can be easily applied to the curing supervision in electronics industry.**

I. INTRODUCATION

After adhesive die attach, the adhesive is cured in a curing oven at specified temperatures to form a tight bond between the die and the leaframe following the manufacturer's recommendation. Different cure schedules are required for different applications for optimal cure [8], [11]. However, the schedule is often determined in a trial and error process in practice because of the lack of process dynamics. Thus, how to optimize the cure schedule is very important to achieve an optimal production including both quality and throughput. The optimal production requires a system-wide cooperation, from control at low-level to supervision at high-level, which often involves detailed knowledge of the process.

The extent of reaction of adhesives during curing, which significantly depends on the temperature, is critical for indicating the strength of the bond. However, on-line sensing techniques for cure content are not available at the present time. On the other hand, temperatures at different locations inside chamber are different due to time-space coupled nature of the thermal process. This makes the measurement of the temperature distribution inside chamber very difficult. Thus, estimating the temperature field with limited sensors is critical and challenging to the optimal cure, especially when the process dynamics is not completely known. Since unsuitable curing temperature may make the curing time longer and result in more defects, maintaining the temperature at every points of the cured object within the specification is critical to the cure quality and throughput. It has no doubt that the coupling effects from multiple heaters used in the chamber will deteriorate the temperature tracking. Theoretically, a decoupling control is useful to a perfect tracking for nonlinear multi-input/multi-output systems. However, the requirement of the inverse process model [13] often makes it impractical because of the process complexity.

In this paper, a model-based systematic framework is proposed for a curing process to achieve an optimal production. First, a realistic model of the curing process is derived with the help of the hybrid spectral/neural method. This technique requires less process knowledge and thus simplifies the traditional modelling. The model developed is effective for cure analysis and control design. An approximate decoupling control is then designed to replace the traditional PID controllers for a better temperature tracking. This technique is effective by avoiding the inversion of the process model, which is often unavailable. Finally, cure supervision is designed and integrated with the local decoupling control. With the help of the process model and cure kinetics of the used adhesive, proper cure temperature and time can be determined either in advance through simulation analyse, or by integration with the local decoupling control in the curing operation. The simulations demonstrate a successful run-by-run control where proper setpoints can be automatically adjusted according to the varying operating conditions.

II. FINITE DIMENSIONAL MODELLING IN SPECTRAL FRAMWORK

A. Fundamental Dynamics

The cure oven considered in this paper has four heaters and four thermocouples in a small 3-dimensional chamber $\{0 \le x \le 0.32$ m, $0 \le y \le 0.288$ m, $0 \le z \le 0.05$ m$\}$ as shown in Fig. 1. The considered curing temperature is around 180 °C. According to Fourier's law of heat transfer [Chapman 1987], the fundamental heat transfer equation of the oven can be expressed approximately as follows:

$$\rho c \frac{\partial T}{\partial t} = \frac{\partial}{\partial x}\left(k \frac{\partial T}{\partial x}\right) + \frac{\partial}{\partial y}\left(k \frac{\partial T}{\partial y}\right) + \frac{\partial}{\partial z}\left(k \frac{\partial T}{\partial z}\right) + f_c(T) + f_r(T) + Q\overline{p} f_u(u(t)) + \overline{D}(t) \quad (1)$$

$$T_m(t) = [\, T(x_1, y_1, z_1, t)\,, \ldots, \; T(x_r, y_r, z_r, t)\,]^T, \quad r = 1, 2, \ldots, m \quad (2)$$

where: x/y/z $\in$ [0, $x_0/y_0/z_0$] --- spatial coordinates (m)

$T = T(x, y, z, t)$ --- Temperature (°C)

$T_m(t)$ --- the measured outputs (°C)

ρ --- Density (Kg/m^3)

c --- Specific heat (J/Kg°C)
k ---Thermal conductivity (W/m°C)

In this model, $f_c(T)$ and $f_r(T)$ are the effects of convection and radiation, respectively, $\overline{D}(t)$ represents the disturbances and unmodelled dynamics, $u(t) = [u_1(t)\ u_2(t)\ u_3(t)\ u_4(t)]^T$ denotes the vector of manipulated inputs, $Q = [q_1(x,y,z)\ q_2(x,y,z)\ q_3(x,y,z)\ q_4(x,y,z)]$ with $q_i(x,y,z)$ being the spatial distribution of the control action $u_i(t)$, and $\overline{p} = diag[p_1\ \ p_2\ \ p_3\ \ p_4]$ is a parameter matrix with p_i being associated with the efficiency and the power of the i-th heater.

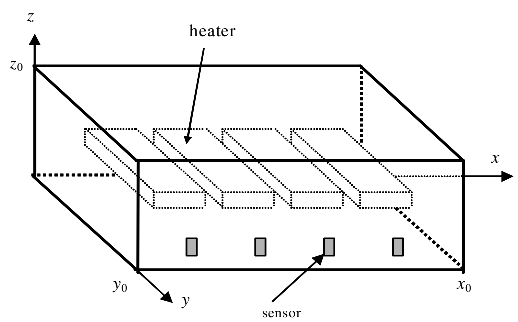

Fig. 1. Simplified configuration of a curing chamber

The chamber walls of the oven are not well-insulated and the boundary conditions are not completely known. For simplicity, the boundary conditions can be described as unknown functions of T, the space coordinates of the oven (x, y, z), and the ambient temperature T_a, respectively as below:

$$k\left.\frac{\partial T}{\partial x}\right|_{x=0} = f_{b1}, \quad -k\left.\frac{\partial T}{\partial x}\right|_{x=x_0} = f_{b2} \tag{3a}$$

$$k\left.\frac{\partial T}{\partial y}\right|_{y=0} = f_{b3}, \quad -k\left.\frac{\partial T}{\partial y}\right|_{y=y_0} = f_{b4} \tag{3b}$$

$$k\left.\frac{\partial T}{\partial z}\right|_{z=0} = f_{b5}, \quad -k\left.\frac{\partial T}{\partial z}\right|_{z=z_0} = f_{b6} \tag{3c}$$

with $f_{b1} = f_1(x, y, z, T, T_a)\big|_{x=0}$, $f_{b2} = f_2(x, y, z, T, T_a)\big|_{x=x0}$.
$f_{b3} = f_3(x, y, z, T, T_a)\big|_{y=0}$, $f_{b4} = f_4(x, y, z, T, T_a)\big|_{y=y0}$.
$f_{b5} = f_5(x, y, z, T, T_a)\big|_{z=0}$, $f_{b6} = f_6(x, y, z, T, T_a)\big|_{z=z0}$.
where: $f_{b1} - f_{b6}$ are unknown nonlinear functions.

Though k and ρ are temperature dependent, equation (1) can still be simplified into linear known dynamics and unknown dynamics $F(T)$. Furthermore, the irregular boundary conditions (3) can also be transformed into homogeneity by moving unknown functions $f_{b1} - f_{b6}$ into unknown dynamics $F(T)$.

$$\frac{\partial T}{\partial t} = k_0\nabla^2 T + Qp_0 f_u(u(t)) + Qpf_u(u(t)) + F(T) + D(t) \tag{4}$$

$$\left.\frac{\partial T}{\partial x}\right|_{x=0} = 0, \quad \left.\frac{\partial T}{\partial x}\right|_{x=x_0} = 0, \quad \left.\frac{\partial T}{\partial y}\right|_{y=0} = 0, \quad \left.\frac{\partial T}{\partial y}\right|_{y=y_0} = 0,$$

$$\left.\frac{\partial T}{\partial z}\right|_{z=0} = 0, \quad \left.\frac{\partial T}{\partial z}\right|_{z=z_0} = 0 \tag{5}$$

where : $\nabla^2 = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2}$, k_0 is the nominal value of $\frac{k}{\rho c}$, p_0 is the nominal value of $\frac{\overline{p}}{\rho c}$, $\frac{\overline{p}}{\rho c} = p_0 + p$ with p as an uncertain parameter matrix, $F(T)$ includes all the unmodelled dynamics and approximations caused from boundary transformation, and $D(t)$ is disturbance. Eq. (4) with (5) is a parabolic partial differential equation (PDE) system with unknown dynamics and homogeneous boundary conditions.

B. Spectral Method Based Neural Modelling

Parabolic PDE systems typically involve spatial differential operators whose eigenspectrum can be partitioned into a finite-dimensional (slow) part and an infinite-dimensional (fast) complement [6], which implies that the dynamic behaviour of such systems can be approximately described by finite-dimensional ordinary differential equation (ODE) systems that capture the dominant (slow) dynamics of the PDE system. The spectral method [1][4][15] widely used in distributed parameter system (DPS) in process control can be applied here to have a time-space separation for the dominant dynamics of the process, with the Galerkin's method for model reduction, and then the neural network is added to compensate unknown dynamics and approximations caused by the separation. This hybrid spectral/neural model is of a low-order structure, and easy for control analysis and design. Using the spectral method [4], the cure process described by the parabolic PDEs in (4) and (5) can be approximated by an N[th]-order time-space separated model as follows.

The eigenvalue problem for operator $\overline{A} = \nabla^2$ in equation (4) can be solved analytically with solutions as below,

$$\lambda_{xi}^2 = \frac{i^2\pi^2}{x_0^2}, \quad \lambda_{yj}^2 = \frac{j^2\pi^2}{y_0^2}, \quad \lambda_{zk}^2 = \frac{k^2\pi^2}{z_0^2},$$

$$X_i(x) = \cos(i\pi x / x_0) \quad Y_j(y) = \cos(j\pi y / y_0) \quad Z_k(z) = \cos(k\pi z / z_0) \tag{6}$$

$$i = 0,1, \ldots ;\ j = 0,1, \ldots ;\ k = 0,1,$$

where λ_{xi}, λ_{yj} and λ_{zk} denote eigenvalues, and $X_i(x)$, $Y_j(y)$ and $Z_k(z)$ denote the corresponding eigenfunctions.

Now the solution of system (4)-(5) can be written as the following orthogonally decoupled (time-space separated) series

$$T(x,y,z,t) = \sum_{i=0}^{\infty}\sum_{j=0}^{\infty}\sum_{k=0}^{\infty}\tilde{a}_{ijk}(t)X_i(x)Y_j(y)Z_k(z) \tag{7}$$

where time function $\tilde{a}_{ijk}(t)$ are expansion coefficients associated with space coordinates (X_i, Y_j, Z_k). Furthermore, the above expression can be organized in the magnitude order of the new eigenvalues $\lambda_n = \lambda^2_{xi} + \lambda^2_{yj} + \lambda^2_{zk}$ with $\lambda_1 > \lambda_2 > \ldots \lambda_n > \ldots$. Thus,

$$T(x,y,z,t)=\sum_{n=1}^{\infty}a_n(t)\phi_n(x,y,z) \quad (8)$$

with eigenfunctions $\phi_n(x,y,z) = X_i(x)Y_j(y)Z_k(z)$, as the spatial basis functions, $a_n(t)$ as its time coefficients.

The infinite dimensional nonlinear system (4)-(5) can be reduced to a set of finite nonlinear ODE system by using the Galerkin's method [5], which minimizes the residual

$$R=\frac{\partial T}{\partial t}-(k_0\nabla^2 T+F(T)+Qp_0 f_u(u(t))+Qpf_u(u(t))+D(t))$$

such that

$$\iiint_{\Omega} RX_i(x)Y_i(y)Z_k(z)dxdydz = 0 \quad (9)$$

where: Ω is defined as the cure domain.

From (9) and by discretization, an approximation to N^{th}-order is obtained for (4) with (5) in discrete form [7]:

$$a(k+1)=Aa(k)+Bu(k)+B\tilde{u}(k)p+f_0(a(k),u(k)) \quad (10a)$$

$$T_m(k)=Ca(k) \quad (10b)$$

where $a(k)=[a_1,a_2,\cdots,a_N]^T$, A= k_0 diag(λ_1, λ_2, …, λ_N)

A, B and C are constant matrices.;

p is an uncertain parameter matrix, and $f_0(a,u)=[f_1(a,u), f_2(a,u),\cdots, f_N(a,u)]^T$ is a vector of unknown dynamics and other approximations.

Actually, A, B, and C in equation (10a) represent the nominal values, and p and $f_0(a(k), u(k))$ represent the uncertainties of the curing process. Based on the above analyses, the coefficients $\{a_n(k), n=1, \ldots, N\}$ can be obtained by solving (10a), from which the temperature distribution at kth step in the oven can be estimated by using

$$T(x,y,z,k)=\sum_{n=1}^{N}a_n(k)\phi_n(x,y,z) \quad (11)$$

To improve the modelling accuracy, a neural network is added at time domain to suppress all the unmodelled dynamics coming from approximation and other unknown dynamics, so that $a_n(k)$ can be more accurately estimated on-line [7]. Based on experimental data, a hybrid general regression neural network model can be constructed and trained either on-line or off-line in discrete-time form as below:

$$a(k+1)=A_n a(k)+B_n u(k)+WG(a(k),u(k)) \quad (12)$$

where: $a(k)=[a_1(k),...,a_n(k)]^T$, A_n, B_n, and W are parameters of the hybrid neural network $G(\bullet)$ is a normalized activation function vector [12]. After training, this hybrid neural model can act independently as the process.

Ten thermocouples are used for modeling and validation as shown in Figure 2, where sensor s1-s4 are used to train the model and the rest of sensors s5-s10 are used to test the model. Because of the symmetry of the oven chamber, only the results of sensor s5-s8 are given in Figure 3. It is clearly seen that the developed model can provide a satisfactory estimation of the temperature distribution.

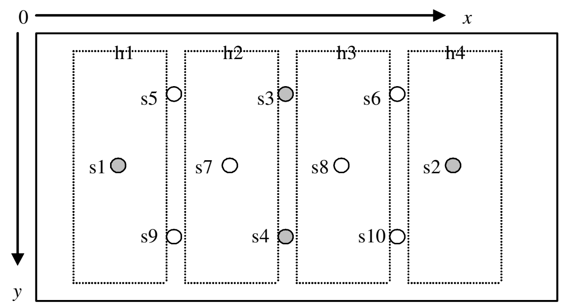

Fig. 2. Sensor locations for modeling and validation

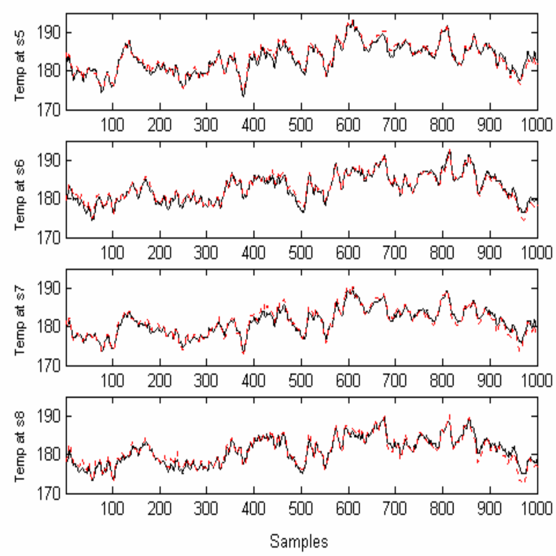

Fig. 3. Performance comparison at (s5, s6, s7, s8)
(Solid/dashed line: measurements/estimates)

III. DECOUPLING CONTROL

With the developed model, cure performance can be easily analysed under different control simulations. As originally designed, four PID controllers are used to control four heaters with four thermocouples located along x-direction at y = 0.14m and z = 0.025m. Because the cure process is nonlinear and strongly coupled, a large overshoot and slow response often appear in the transient performance of PID control. Thus, an effective decoupling control needs to be developed. For the oven system described by (12) with four temperature measurements as $T_m(k)=Ca(k)$, the input-output relationship can be expressed as follows:

$$T_m(k+1)=CA_n a(k)+C(B_n u(k)+WG(a(k),u(k))) \quad (13)$$

and can be written as a function of a(k) and u(k),

$$T_m(k+1)=f(a(k),u(k)) \quad (14)$$

The tracking error can be defined as $e(k) = r(k)-T_m(k)$ with the reference trajectory as $r(k)$. Since the oven process is minimum phase, if the explicit inversion of $f(a(k),u(k))$ exists, we can find $u(k)=f^{-1}(a(k),v)$ to obtain decoupled linear dynamics. It is well-known that the dynamic inversion is difficult to obtain for the complex process like (14). However, the Taylor series of $f(a(k),u(k))$ at u(k-1) can be easily derived as follows:

$$T_m(k+1) = f(a(k),u(k))$$
$$= f(a(k),u(k\text{-}1)) + f_1(u(k)\text{-}u(k\text{-}1)) + \varepsilon_k \qquad (15)$$

with $f_1 = \frac{\partial f(a(k),u(k-1))}{\partial u(k)}$ and $\varepsilon_k = O^2(gk)$ and $||\varepsilon_k|| \le \varepsilon_0$.

Since f_1 is non-singular for the neural model (12), an approximate input/output linearization is proposed here by choosing the following adaptive control law

$$u(k) = u(k\text{-}1) + gk \qquad (16)$$

with $gk = f_1^{-1}(w(k)+se(k))$ and $w(k) = r(k+1) - f(a(k),u(k\text{-}1))$. Then, we can obtain the tracking error dynamics as

$$e(k+1) + se(k) = -\varepsilon_k \qquad (17)$$

The tracking error e(k) will be bounded since $|s_i| < 1$ and ε_k is bounded.

In the adaptive decoupling control law (16) and the temperature estimation (11), the states $a(k)$ are required, which however are unknown in practice due to finite number of sensors used. The so called extended Kalman observer (EKO) will be used to estimate the states of the cure process. The algorithm [2] is adopted in the control system because of its good estimation performance. As shown in Figure 4, a very satisfactory tracking performance is achieved by the proposed decoupling control scheme. Compared with PID controllers, there is almost no overshoot in a faster response.

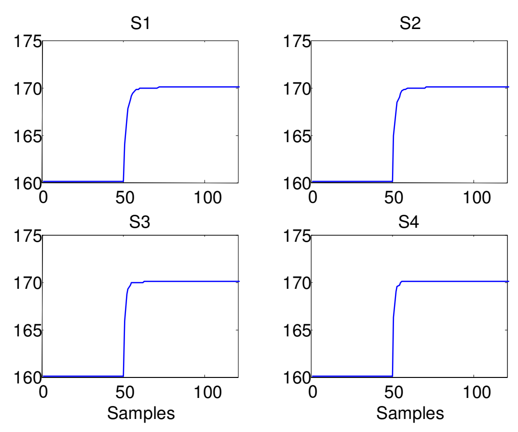

Fig. 4. Decoupling control performance

IV. MODEL BASED SUPERVISION

A. Process Requirement

The cure kinetics of commonly used die attach adhesives [9,14] can be described as follows:

$$\frac{d\alpha}{dt} = \gamma_0 e^{-\frac{E_A}{RT}}(1-\alpha)^n \qquad (18)$$

where, α is the extent of reaction, dα/dt is rate of reaction, n is the order of reaction, γ_0 is the reaction rate constant at infinite temperature, E_A is the activation energy, T is the temperature in Kelvin, and R is the gas constant = 8.314 J/mol·K. Based on the cure kinetics equation with the known activation energy and reaction order, the extent of reaction will be determined by solving the above equation (18) for a class of die attach adhesives. The extent of reaction was used to determine the minimum and maximum time of curing. The time required to reach extent of reaction 90% is the minimum time for developing sufficient mechanical strength, and that to reach 95% extent of reaction is considered as the maximum time to avoid the material degradation and also to satisfy the manufacturing economics [14].

Due to the nature of the thermal distribution, different locations of the chamber will have different temperature, and thus resulting in the maximum T_{max} and minimum temperature T_{min} inside the chamber. This may affect the cure quality because different temperatures obtained on the cured object surface. Suppose that Tc_{max} and Tc_{min} are pre-specified maximum and minimum cure temperature in the curing area, respectively. Obviously, we must have $T_{max} \le Tc_{max}$ and the cure time can then be calculated from equation (18) with the corresponding T_{min}.

There are two main issues in electronics manufacturing industry, quality and throughput. An optimal cure schedule, which is closely associated with die attach adhesives and dynamics of the oven, is very important for both high quality bonds and maximum throughput. Usually, an oven can accommodate a number of leadframes and each leadframe contains many dies after adhesive die attach. Assuming that the oven can accommodate M leadframes simultaneously for cure time t_c (seconds). The throughput, J (number of leadframes/hour) with guaranteed strength of the bonds, is calculated as

$$J = 3600M / t_c \qquad (19)$$

which can be maximized by decreasing t_c. According to equation (18), t_c is a function of α and T_{min}. Decreasing t_c is equivalent to increasing T_{min}, which requires a higher temperature setpoint, and consequently pushes T_{max} higher. However, this adjustment must be constrained by the specified Tc_{max} for the cure quality, which is often made in a trial and error process.

B. Neural Model Based Supervision

The model-based systematic approach is described in Figure 5. The neural model (12) can be used as the simulation platform. The model is also used to estimate the curing temperature distribution, upon which the setpoints can be optimized according to the cure kinetics of the used adhesives. At low-level, the new decoupling control is used and has a fast and good tracking. At the high-level, a proper cure strategy is developed to optimally and automatically tune the control setpoints for a more consistent temperature for all parts of the cured object. The combination of these two actions will result in an effective run-by-run control. The developed supervision system can provide proper setpoints for the low-level decoupling controller automatically according to varying working conditions and to complete the cure task upon the estimated extent of reaction α.

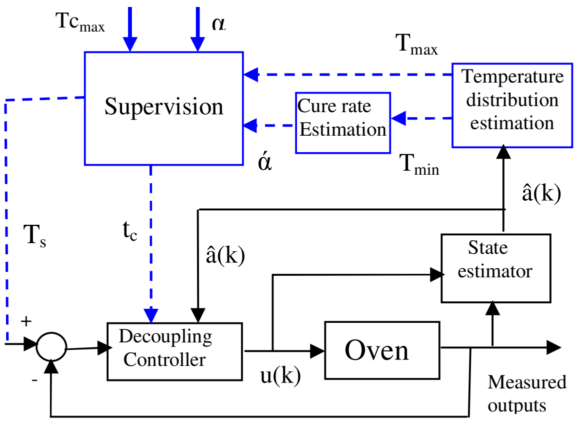

Fig. 5. Integrated control and supervision of the process

Off-line Setpoint Optimization

To achieve a balance between throughput and quality, the temperature distribution T should be controlled to be within a required range (Tc_{min}, Tc_{max}), where Tc_{max} is for quality concern and Tc_{min} for throughput concern. Thus, a closed-loop control is required to search for optimal setpoints. A discrete-time PID controller from [10] can be easily used for this purpose.

$$Ts(k+1)=Ts(k)+Kp[e(k)-e(k-1)]+K_I e(k)$$
$$+K_D[e(k)-2e(k-1)+e(k-2)] \quad (20)$$

where $e(k)=Tc_{max}-T_{max}(k)$; Ts(k) is the setpoint; Tc_{max} is the pre-specified maximum temperature; $T_{max}(k)$ is the estimated maximum temperature; Kp, K_I, and K_D are three parameters in the PID controllers.

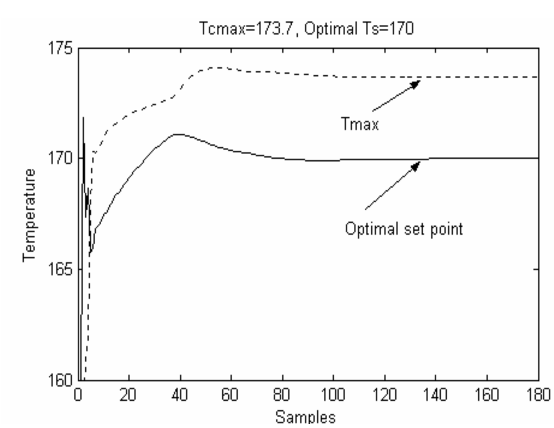

Fig. 6. Setpoint optimization in the closed-loop

Given a required Tc_{max}, the optimal setpoint will be the steady-state result of the closed-loop control. As shown in Figure 6, the optimal setpoint is stable at 170°C for the given Tc_{max}=173.7°C. Afterwards, the corresponding T_{min} in the cure area can be estimated (169.54°C), then the cure time tc from (18) with T_{min} and specified α (i.e. α = 0.95), and finally the throughput from (19).

Optimal Cure in Run-by-run Operation

The on-line supervision method proposed in Figure 5 might be useful to the optimal cure, where the oven model (12) is for estimating T_{max} and T_{min} of the cured area, and the cure kinetics of the adhesive (18) is for estimating the extent of reaction α. Once the working conditions change during the operation, the setpoints can be adjusted automatically to meet the optimal cure requirement.

Suppose that a two-phase cure schedule is designed under Tc_{max}=173.7 C° as shown in Table 1, where the T_s in phase 1 is given as 160 C°. The optimal T_s in phase 2 is calculated as 170C° in advance using the simulation given in the previous section.

Table 1: Cure schedule

	Phase 1	Phase 2
Setpoint T_s	160 C°	170 C°
duration	10 min	15 min

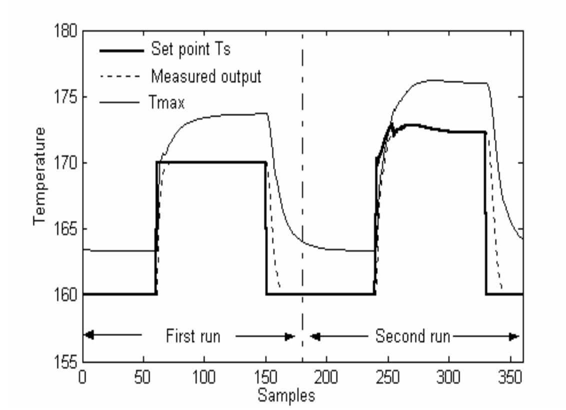

Fig. 7. Setpoint optimization upon changing conditions

The run-by-run simulation in Figure 7 shows that the cure temperature can track the optimal setpoint T_S very well under the decoupling control during the first run, with the maximum temperature T_{max} in the curing area clearly under Tc_{max} =173.7 C°.

Assuming the working conditions change after the first run, with the given Tc_{max} moving to 176 C°. Then, the designed optimal supervision at outer loop will automatically adjust T_s a bit higher in the second run as shown in Figure 7 for the purpose of the optimal production; while the decoupling controllers at the inner loop still maintains a good tracking of the new setpoint T_s. The maximum temperature T_{max} in the curing area is clearly controlled under Tc_{max} =176 C°.

Cure Termination Control

The varying operating conditions may disturb the cure time t_c that is usually pre-specified. Since the cure time t_c is associated with the extent of reaction, and the extent of reaction α can be estimated from the estimated T_{min} and T_{max}, thus the cure schedule can be adjusted on-line with the developed model.

Suppose the cure conditions are given below,

Cure kinetics: n=3, E_A=260 (KJ/mol).

Cure schedule: A three-phase curing given in Table 2.

Disturbances: The disturbances happen at sample 120.

Table 2: A three-phase cure schedule

	Phase 1	Phase 2	Phase 3
Setpoint T_s	160 C°	170 C°	180 C°
Duration (min)	10	20	30

The extent of reaction is estimated in Figure 8. If α = 0.9 is specified as the complete curing, then the cure time t_c is about 280 samples. If α = 0.95 is specified as the complete curing, the cure schedule should be modified. This is because the extent of reaction α reaches 0.95 very slowly under the given cure schedule. The curing temperature may need to be increased or the curing time to be longer. It is worth noting that, with the developed model, the proper cure time can be estimated on-line or off-line.

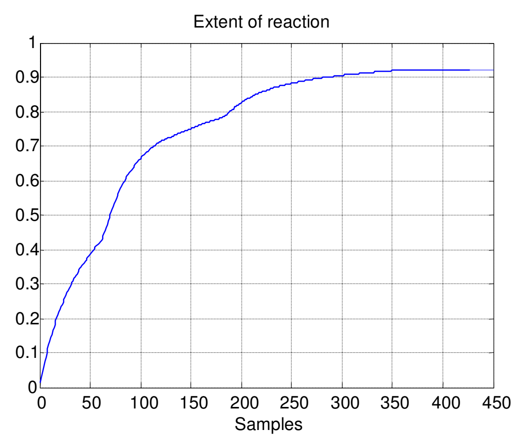

Fig. 8. Estimated extent of reaction during curing

V. CONCLUSIONS

The paper proposes a novel concept to integrate cure schedule optimization and decoupling control using the process model for an optimal production. A hybrid spectral/neural method is first used to model the process for estimating the temperature field. The developed approximate decoupling controller thereafter can maintain a better temperature tracking. The optimal cure schedule of the process can be systematically determined instead of using a trial and error method. The proposed approach can be readily used for different cure processes provided that the models of those processes are available.

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