Brief Paper

Terminal iterative learning control with an application to RTPCVD thickness control

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Abstract

A special type of iterative learning control (ILC) problem is considered. Due to the insufficient measurement capability in many real control problems such as Rapid Thermal Processing (RTP), it may happen that only the terminal output tracking error instead of the whole output trajectory tracking error is available. In the RTP chemical vapor deposition (CVD) of wafer fab. industry, the ultimate control objective is to control the deposition thickness (DT) at the end of the RTP cycle. The control profile for the next operation cycle has to be updated using the terminal DT tracking error alone. A revised ILC method is proposed to address this terminal output tracking problem. By parameterizing the control profile with a piecewise continuous functional basis, the parameters are updated by a high-order updating scheme. A convergence condition is obtained for a class of uncertain discrete-time time-varying linear systems including the RTPCVD system as the subset. Simulation results for an RTPCVD thickness control problem are presented to demonstrate the effectiveness of the proposed iterative learning scheme. © 1999 Elsevier Science Ltd. All rights reserved.

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1. Introduction

Rapid thermal processing (RTP) systems are single-wafer, cold-wall chambers that utilize one or more radiant heat sources to rapidly heat up the semiconductor substrate at high temperatures for short times (Roozeboom and Parekh, 1990). In semiconductor wafer fab. industry, RTP has been used as a versatile single-wafer processing technique for various thermal processing applications. Single-wafer processing will be preferred over conventional batch equipment for many applications as the wafer size increases beyond 150–200mm. Factors in favor of single-wafer processing include compatibility with multi-chamber cluster equipment for vacuum-integrated processing, improved fabrication cycle time, and enhanced fabrication process repeatability due to improved process control. One of the typical RTP systems is for the chemical vapor deposition (RTPCVD). The terminal deposition thickness (DT) for each run of RTPCVD is to be controlled within a given tolerance by adjusting the heating lamp power profile (Chen, Xu, Lee & Yamamoto, 1997b).

It is critical to maintain a uniform temperature profile across the wafer during steady-state and transient operation to avoid the generation of slip dislocations and to ensure process uniformity. The process control can be divided into a three tier hierarchical model consisting of

- supervisory control,
- run-to-run (RtR) control, and
- real-time control.

Supervisory control, at the highest level, influences changes on a lot-to-lot basis. Run-to-run control updates occur after each wafer is processed. In supervisory and RtR control, only off-line sensors are required for the desired measurements which are often unavailable in...
situ. Real-time control can often be subdivided into wafer state and process state control. Wafer state refers to physical quantities associated with the processed silicon wafer (e.g. spatial temperature distribution, film thickness, etc.). Process state, on the other hand, refers to physical quantities which are not wafer parameters (e.g. reactor wall temperatures, partial pressures of gases, etc.). Badgwell et al. provide a comprehensive survey of modeling and control issues in the semiconductor industry (Badgwell et al., 1995). From application examples, it is apparent that the entire hierarchy may or may not be required for a particular semiconductor application. In this paper, we concentrate on the control in the RtR level. Some works exist (Mozumder, Saxena & Collins, 1994; Zaﬁriou, Adomaitis & Gattu, 1995) for a better run-to-run control using the idea of numerical optimization. In this paper, a new scheme — “terminal iterative learning control” is proposed for RTPCVD application.

As the RTPCVD system executes a given task repeatedly, this repeatability can be utilized to improve the system control performance by the iterative learning control (ILC) method (Arimoto, Kawamura & Matsuakl, 1984; Moore, 1993). The conventional ILC task is to follow a desired output trajectory in a given time interval through learning iteratively. In RTPCVD, however, the problem cannot be formulated in such conventional way because the exact measurement of wafer temperature is almost impossible (Peyton, Kinoshita, Lo & Kwong, 1990). In a more general framework, this class of control problems can be classified as the PTP (point-to-point) control problem. The main features of a PTP problem are: (1) the only available measurement is the terminal state or terminal output; (2) the ultimate control objective is also the terminal state or terminal output instead of the whole trajectory of the system. The precise PTP control finds increasing applications in flexible manipulators (Bhat and Miu, 1992), mobile robots (Oriolo, Panzieri & Ulivi, 1996) and so on. Learning method has been applied to PTP control problems successfully in (Oriolo et al., 1996; Lucibello, 1994). The key technique is to represent the control function as a linear combination of a pre-determined piecewise continuous functional basis (orthogonal polynomials, splines etc.) and then to update the coefficient vector iteratively based on the terminal output error measurement at the end of each run (system repetition).

Motivated by RTPCVD control problem, in this paper we developed a terminal ILC scheme to deal with a class of uncertain discrete-time linear time-varying systems in general and the RTPCVD problem in particular. A sufﬁcient convergence condition of the terminal ILC is obtained. Terminal tracking performance under disturbance is also investigated in this paper. Simulation studies with an RTPCVD model demonstrate the effectiveness of the proposed terminal iterative learning control scheme. Moreover, it is also shown that a high-order learning updating scheme can provide a better convergence performance.

This paper is organized as follows. The RTPCVD model is introduced in Section 2 which is linearized and discretized into a linear time-varying discrete-time system. In Section 3, the high-order iterative terminal learning control scheme is derived with the convergence analysis. Simulation results are presented in Section 4 to illustrate the effectiveness of the method proposed in this paper. Concluding remarks are given in Section 5.

2. RTPCVD model and control problem

Consider a simplified RTPCVD model of poly-Si which includes the temperature dependence of deposition rate (Gyurcsik, Riley & Sorvell, 1991; Zaﬁriou et al., 1995), as follows:

$$\frac{d T_w}{dt} = \frac{[\sigma A_w E_u ( T_{amb}^4 - T_w^4) + f E_w Q P] / M_w}{\gamma / R T_w}$$

where the meanings of variables and the relevant parameters are given in Table 1. $T_w(0)$ is known and $S(0) = 0 \mu m$.

The control objective is to find a lamp power profile $P(t)$ such that the controlled wafer temperature $T_w(t)$ follows a pre-planned trajectory $T_w^*(t)$ as closely as possible in a given time interval $[0, NT_s]$, where $T_s$ is the sampling period and $N$ is the number of samples. $T_w^*(t)$ is pre-designed (Zaﬁriou et al., 1995) to satisfy the RTP requirements and especially to guarantee the final deposition thickness $S(T)$ ($T = NT_s$). However, conventional feedback-based control schemes are hardly applicable to this control task because the in situ measurement of wafer temperature $T_w(t)$ is an even tougher problem. A practical way is to use the measurement of the terminal DT at the end of each run. The control task then becomes: given the RTP cycle period $T$ and a desired DT $S_d(T)$, with the repetitive RTP runs, iteratively update the control $P(t)$ based on the terminal DT tracking error $e(T) = S_d(T) - S(T)$.

The basic idea is to parameterize the control function $P(t)$ using some known basis functions. The parameters are to be determined through an iterative learning law. The learning gain should be properly chosen to guarantee the convergence of learning process. To simplify the analysis and design, one may linearize (1) around an equilibrium point $(T_w^*(t), S^*(t), P^*(t))$. In practice, one may use an approximate equilibrium point as shown in the simulation study in Section 4.2. A small variation around the equilibrium point is denoted by $(\Delta T_w(t), \Delta S(t), \Delta P(t))$. 

The linearized system is
\[
\frac{d\Delta T_w}{dt} = \left[ -4\sigma A_w E_w (T_w^*)^3 \Delta T_w + f E_w Q \Delta P \right]/M_w + w_1(t),
\]
\[
\frac{d\Delta S}{dt} = k_0 \frac{\gamma}{R} \exp \left( -\frac{\gamma}{RT_w} \right) \Delta T_w/(T_w^*)^2 + w_2(t),
\]  \tag{2}
where \(w_1(t), w_2(t)\) are high-order terms which can be taken as the modeling uncertainties. As the process is computer-controlled, a discretized model is preferred for the analysis. Define the states \(x_1 = \Delta T_w, x_2 = \Delta S\) and control \(u = \Delta P\). Discretizing (2) with a zero-order hold (ZOH) gives
\[
x_{t+1} = A(t)x_t + B(t)u_t + w_t(t),
\]
\[
y_t = x_2(t) + v_t(t),
\]  \tag{3}
where \(t = 0, 1, \ldots, N; x = [x_1, x_2]^T\); \(A(t)\) and \(B\) are matrices with appropriate dimensions in terms of (2); \(w(t)\) is the modeling uncertainty related to \(w_1(t)\) and \(w_2(t)\); \(v(t)\) is the measurement noise (only \(v(N)\) is concerned). In the subsequent section, a terminal iterative learning control method is developed for this class of uncertain linear time-varying discrete-time systems.

3. Terminal output tracking by iterative learning

Consider in general the uncertain time-varying linear discrete-time system
\[
x_{t+1} = A(t)x_t + B(t)u_t + w_t(t),
\]
\[
y_t = C(t)x_t + v_t(t),
\]  \tag{4}
where \(t = 0, 1, \ldots, N; \) the subscript \(i\) indicates the system repetition number; \(x_{t}(t) \in \mathbb{R}^n; \) control function \(u_{t}(t) \in \mathbb{R}^m; \) output \(y_{t}(t) \in \mathbb{R}^p; \) \(w_t\) and \(v_t\) are model uncertainty and measurement disturbance, respectively. During the repetitive operations, only \(y_{t}(N)\) is measurable at the end of every run \(i\). The control task is to find and improve the control function \(u_{t}(i)\) in an iterative manner such that \(y_{t}(N)\) approaches to a given terminal output \(y^d\) as \(i\) increases.

To restrict our discussion, the following assumptions are imposed:

(A1) System (4) is completely controllable.

(A2) The initial state \(x_{t}(0)\) at every iteration \(i\) can be repositioned nearby the same starting point with some misalignment
\[
\|\Delta x_{t+1}(0)\| \leq \varepsilon_1,
\]
where \(\varepsilon_1\) is a small positive constant. \(\|\cdot\|\) is an appropriate norm for a vector. Accordingly, an induced norm can be defined for a matrix. For example, given a vector \(f = [f_1, \ldots, f_n]^T\) and a matrix \(G = [g_{ij}]_{m \times n}\), the norms are defined as follows:
\[
\|f\| = \max_{1 \leq i \leq n} |f_i|, \quad \|G\| = \max_{1 \leq i \leq m} \left( \sum_{j=1}^{n} |g_{ij}| \right).
\]

(A3) The disturbance and modeling error are bounded and
\[
\|\Delta w_{t+1}(N)\| \leq \varepsilon_2, \quad \|\Delta v_{t+1}(N)\| \leq \varepsilon_3.
\]
Here \(\Delta w_{t+1}(t) = w_{t+1}(t) - w_t(t)\) and \(\Delta v_{t+1}(t) = v_{t+1}(t) - v_t(t)\); \(\varepsilon_2\) and \(\varepsilon_3\) are small positive constants.

Assumption (A1) assures the existence of control for the given \(y^d\). The initial states are not necessary to be strictly repetitive according to (A2). (A3) is a relaxed assumption on the uncertainty \(w_{t}\) and disturbance \(v_{t}\). It is well known that any ILC scheme is able to remove repeatable uncertainty or disturbance. Thus we only need to know the “variations” of the disturbances in any two consecutive cycles. Assumption (A3) describes the bounds of such variations.

As the tracking control task is only for the terminal output, conventional ILC updating law (Arimoto et al., 1984) cannot be applied. Following the idea of dynamic fitting (Chen, Wen, Gong & Siu, 1997a), instead of solving a functional minimization problem, we parameterize the control \(u_{t}(i)\) as
\[
u_t(i) = \Phi(t) \Xi_i, \tag{5}
\]
where \(\Xi_i = [\xi_{1i}, \ldots, \xi_{mi}]^T \in \mathbb{R}^{p \times 1}\) is the parameter vector; \(\Phi(t) = [\phi_1(t), \ldots, \phi_m(t)]^T \in \mathbb{R}^{m \times p}\) is a properly chosen basis function matrix. \(\phi_j(t) = [\phi_{j1}(t), \ldots, \phi_{jm}(t)]^T, \ j = 1, \ldots, m\). The task is hence converted into finding an iterative scheme based on the observation of the terminal output tracking error \(e_t(N) = y^d - y_t(N)\) such that the parameter \(\Xi_i\) converges as \(i\) increases and meanwhile \(e_t(N)\) converges to a prescribed ball centered at the origin.

By solving Eq. (4), one obtains the terminal state
\[
x_{t}(N) = G x_{t}(0) + H \Xi_i + w_{t}(N), \tag{6}
\]
where
\[
G = \prod_{t=0}^{N-1} A(t), \tag{7}
\]
\[
H = \sum_{k=1}^{N} \prod_{j=1}^{k-1} A(N - j) B(N - k) \Phi(N - k), \tag{8}
\]
\[
w_{t}(N) = \sum_{k=1}^{N} \prod_{j=1}^{k-1} A(N - j) w_{t}(N - k) \tag{9}
\]
with dimensions \(G \in \mathbb{R}^{n \times n}, H \in \mathbb{R}^{n \times p}\) and \(w_{t}(N) \in \mathbb{R}^{n \times 1}\). Thus the terminal output becomes
\[
y_{t}(N) = CG x_{t}(0) + CH \Xi_i + Cw_{t}(N) + v_{t}(N). \tag{10}
\]
Investigating the terminal tracking error of the output \( y_t(N) \), one can easily get the relation between two consecutive operation cycles.

\[
e_{t+1}(N) = y^d - y_{t+1}(N) = e(N) - (y_{t+1}(N) - y_t(N))
\]

\[
= e(N) - C G \Delta x_{t+1}(0) - C H \Delta \xi_{t+1}
- C \Delta w_{t+1}(N) - \Delta v_{t+1}(N),
\]

(11)

where \( \Delta h_{t+1} = h_{t+1} - h_t \), \( h_t \in \{x(0), \xi_t\} \).

The high-order learning updating law is proposed as follows:

\[
\xi_{t+1} = \xi_t + \Delta \xi_{t+1} = \xi_t + \sum_{k=1}^{M} L_k e_{t-k+1}(N),
\]

(12)

where \( M \) is the order of ILC and \( L_0, L_1, \ldots, L_M \) are learning gain matrices which are to be specified in applications. Substituting Eq. (12) into Eq. (11) yields

\[
e_{t+1}(N) = (I_r - C H L_1) e_t(N) - C G \Delta x_{t+1}(0)
- C H \sum_{k=2}^{M} L_k e_{t-k+1}(N) - C \Delta w_{t+1}(N) - \Delta v_{t+1}(N),
\]

(13)

where \( I_r \) is an \( r \times r \) unit matrix.

To analyze the convergence of the proposed terminal learning control, an additional assumption is required.

(A4) \( CH \) has a full row rank.

The key issue in (A4) is related to the existence of the control for PTP control and has been well discussed in Bhat and Miu (1991). As indicated in Bhat and Miu (1991), a proper choice of \( \Phi(t) \) is always possible if system (4) is controllable.

**Remark 3.1.** Consider the case when system (4) is LTI and the relative degree is \( d_r \). We know that \( CA^tB = 0 \), \( j = 0, 1, \ldots, d_r - 1 \). Referring to Eq. (8),

\[
CH = \sum_{k=1}^{N} CA^{N-k}B \Phi(N-k).
\]

Hence, for a properly chosen \( \Phi \), \( CH \) can be made full rank if \( d_r < N \). Usually, the number of sampling points is much larger than the relative degree. Thus, (A4) can be satisfied easily.

**Remark 3.2.** Regarding the \( \Phi \) selection, in general, only assumption (A4) needs to be satisfied. In practice, to choose a suitable \( \Phi(t) \), we need to have some knowledge about the system to be controlled. \( \Phi \) can be chosen in terms of the particulars of the plant so as to further improve the control performance. A detailed example is presented in Section 4.

We summarize the above discussion in the following theorem.

**Theorem 1.** Consider system (4) under assumptions (A1)-(A4) with a given achievable terminal output \( y^d \). By applying the control functional parameterization (5) and the iterative learning updating law (12), through the repetitive operations, the terminal tracking error \( e_t(N) \) will converge to a bound if

\[
\rho \triangleq \sum_{k=1}^{M} \rho_k < 1, \quad (14)
\]

where

\[
\rho_1 = \max_{x(0)} ||I_r - C H L_1||,
\]

\[
\rho_k = \max_{x(0)} ||C H L_k||,
\]

\( k = 2, 3, \ldots, M \).

The convergence bound is

\[
||e_t(N)|| \leq e^*; \quad \text{(15)}
\]

where

\[
e^* \leq (||C G|| e_1 + ||C|| e_2 + e_3)(1 - \rho). \quad \text{(16)}
\]

Clearly, \( e^* \) is a class-K function of \( e_1, e_2 \) and \( e_3 \) which implies that \( e^* \to 0 \) as \( e_1, e_2 \) and \( e_3 \) approach 0.

To give a proof of the above theorem, the following lemma is required.

**Lemma 2.** Suppose a real positive series \( \{a_i\}_{i=1}^{\infty} \) satisfies

\[
a_{i+1} \leq \rho_1 a_i + \rho_2 a_{i-1} + \cdots + \rho_M a_{i-M+1} + \varepsilon, \quad (i = M + 1, M + 2, \ldots) \quad \text{(17)}
\]

where \( \rho_i \geq 0 \), \( i = 1, 2, \ldots, M \), \( \varepsilon \geq 0 \). If

\[
\rho = \sum_{i=1}^{M} \rho_i < 1, \quad \text{(18)}
\]

the following holds:

\[
\lim_{i \to \infty} a_i \leq \varepsilon/(1 - \rho). \quad \text{(19)}
\]

**Proof.** See (Chen, Gong & Wen, 1998). \( \square \)

Now we proceed to present a proof of Theorem 1.

**Proof.** Taking norm operation of Eq. (13) gives

\[
||e_{t+1}(N)|| \leq \sum_{k=1}^{M} \rho_k ||e_{t-k+1}(N)|| + ||C G|| e_1
+ ||C|| e_2 + e_3. \quad \text{(20)}
\]
Comparing with Eq. (17), we have the analogy if defining $a_i = \|e_i(N)\|$ and $\varepsilon = \|CG\|e_1 + \|C\|e_2 + \varepsilon_3$. By virtue of condition (14),

$$\lim_{i \to \infty} e_i(N) \leq \varepsilon/(1 - \rho) \triangleq \varepsilon_0.$$  \hspace{1cm} (21)

**Remark 3.3.** If the uncertainty $w(t)$ is repeatable from run to run, their effects on the ILC can be completely rejected according to Theorem 1. The high-order terms $w_1(t), w_2(t)$ in the linearized model (2) can be regarded as repetitive when a good initial control is used.

**Remark 3.4.** The boundedness of trajectories during each run is guaranteed theoretically because only a finite time interval is concerned in every run. However, in practice, it may happen that the tracking errors in between sampling points are large while maintaining a good pointwise tracking. In such cases, properly choosing $\Xi^{(0)}$ and $\Phi(t)$ is essential. Fully utilizing the known information about the system may be helpful as shown in the simulation study presented in Section 4.

### 4. Application example

#### 4.1. RTPCVD model

In the following, the terminal iterative learning control scheme developed above is applied to RTPCVD thickness control problem in the wafer fab. process. To simulate the actual situation, an RTPCVD model with the quartz window effect is considered:

$$\frac{dT_w}{dt} = \sigma A_w E_w(T_q^4 - T_{w}^4) + f E_w Q P / M_w,$$

$$\frac{dT_q}{dt} = (Q P + h A_q (T_{amb} - T_q)) / M_w,$$

$$\frac{dS}{dt} = k_0 \exp \left( - \frac{\gamma}{RT_w} \right),$$

where the related parameters are listed in Table 1. In ILC design, however, we assume that only the simplified model (1) is available. The initial states are $T_w(0) = T_q(0) = 300^\circ K$, $S(0) = 0 \mu m$ and $N = 220$ s. The desired final DT (deposition thickness) is $S(T) = 0.5 \mu m$. The objective is to find the lamp power profile $P(t)$. A well pre-designed wafer temperature profile (Chen et al., 1997b) can be used. Such a wafer temperature profile will give a final DT of 0.5 $\mu m$. However, online measurements of $T_w(t)$ are not available for the closed-loop control. To overcome the difficulty in $T_w(t)$ measurement we apply the proposed terminal ILC method which only requires the terminal DT measurement.

#### 4.2. Terminal ILC

To make the problem tractable, control function $P(t)$ is parameterized by

$$P(t) = \Phi(t) \Xi = \sum_{j=1}^{p} \phi_j(t) \xi_j,$$  \hspace{1cm} (23)

### Table 1

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Meaning</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_q$</td>
<td>400</td>
<td>Quartz window area</td>
<td>cm$^2$</td>
</tr>
<tr>
<td>$A_w$</td>
<td>400</td>
<td>Wafer area</td>
<td>cm$^2$</td>
</tr>
<tr>
<td>$E_w$</td>
<td>0.8</td>
<td>Wafer emissivity</td>
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</tr>
<tr>
<td>$f$</td>
<td>0.5</td>
<td>Lamp power absorbed by wafer</td>
<td>unitless</td>
</tr>
<tr>
<td>$\varepsilon$</td>
<td>Heat transfer coefficient for forced convection</td>
<td>cal/cm$^2$/s/K</td>
<td></td>
</tr>
<tr>
<td>$P$</td>
<td>$\varepsilon [0, 1]$</td>
<td>Lamp power control factor</td>
<td>unitless</td>
</tr>
<tr>
<td>$Q$</td>
<td>1076</td>
<td>Lamp power constant</td>
<td>cal/s</td>
</tr>
<tr>
<td>$R$</td>
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<td>Gas constant</td>
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</tr>
<tr>
<td>$S$</td>
<td>Polysilicon deposition thickness</td>
<td>$\mu m$</td>
<td></td>
</tr>
<tr>
<td>$T_w$</td>
<td>Wafer temperature</td>
<td>K</td>
<td></td>
</tr>
<tr>
<td>$T_q$</td>
<td>Quartz window temperature</td>
<td>K</td>
<td></td>
</tr>
<tr>
<td>$T_{amb}$</td>
<td>Ambient temperature</td>
<td>K</td>
<td></td>
</tr>
<tr>
<td>$M_w$</td>
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<td>Wafer thermal mass</td>
<td>cal/K</td>
</tr>
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<td>$M_q$</td>
<td>100</td>
<td>Quartz window thermal mass</td>
<td>cal/K</td>
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<tr>
<td>$k_0$</td>
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<td>Pre-exponential constant of polysilicon deposition</td>
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<tr>
<td>$\gamma$</td>
<td>39200</td>
<td>Activation energy of polysilicon deposition</td>
<td>cal/g mol</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>$1.356 \times 10^{-12}$</td>
<td>Boltzmann constant</td>
<td>cal/(s cm$^2$ K$^2$)</td>
</tr>
</tbody>
</table>

$h A_q \triangleq 1.84$ cal/s/K
where \( \phi_j(t) \) \((j = 1, ..., p)\) are known basis functions and \( \xi_j \) \((j = 1, ..., p)\) are control parameters to be determined through iterative learning. The first-order updating law for \( \Xi \) is that
\[
\Xi_i = \Xi_{i-1} + L_1 e_{i-1}(N),
\]
(24)
where \( i \) is the iteration number and \( L_1 \) is the learning gain matrix to be designed. The design is based on the learning convergence condition discussed in Theorem 1 and the available a priori knowledge about the system as shown in the following.

It should be pointed out that a good choice of \( \Phi(t) \) and \( \Xi_0 \) is important to the above scheme. Although the actual RTPCVD process is complex, the simplified model (1) is still useful in choosing a good \( \Phi(t), \Xi_0 \) and \( L \). As the \( S(t) \) is a monotonically increasing function, one may approximate it as a quadratic polynomial or an exponential function with two unknowns which can be determined by two known conditions \( S(T) \) and \( T_a(0) \). Hence, with this known \( S(t) \), one may get \( T_w(t) \) and \( P(t) \) which in turn can be used to determine \( \Phi(t) \) and \( \Xi_0 \). For example, setting \( S(t) = \alpha(e^{\beta t} - 1) \),
\[
\alpha(e^{\beta t} - 1) - 1) = S_0(t),
\]
(25)
one can calculate \( \alpha, \beta \) by first equating
\[
dS(t)/dt|_{t=0} = \alpha \beta = k_0 \exp(-\gamma/[RT_w(0)]),
\]
(26)
and solving Eq. (26) through numerical iterations. Immediately, one can get from the second equation of Eq. (1) that
\[
T_w(t) = 1/(\alpha' + \beta'),
\]
(27)
where \( \alpha' = -R[\ln(\alpha'\beta/k_0\gamma)]/\gamma \) and \( \beta' = -R\beta/\gamma \). By substituting \( T_w(t) \) into the first equation of Eq. (1), the control can be written in the following form:
\[
P(t) = c_0 + c_1(\alpha' + \beta')^2 + c_2(\alpha' + \beta')^4,
\]
(28)
where \( c_0, c_1, c_2 \) are known constants based on Eq. (1) and Table 1. In the following, the triple \( (S(t), T(t), P(t)) \) in Eqs. (25), (27) and (28), respectively, are chosen as the approximated equilibrium \( (T_w^*(t), S^*(t), P^*(t)) \).

The above simple derivation shows that a proper choice of \( \Phi(t), \Xi_0 \) can be made based on the simplified model.

From the above discussions, the lamp power profile \( P(t) \) is parameterized according to Eq. (28) where \( c_0 = -0.0082; c_1 = 2.8 \times 10^{-8}; c_2 = 1.01 \times 10^{-12}; \alpha' = 0.003; \beta' = -1.202 \times 10^{-5} \) based on Eq. (28). Now we can set \( \Phi(t) = [1, 1/(\alpha' + \beta')^2, 1/(\alpha' + \beta')^4] \) as the basis function and set \( [c_0, c_1, c_2] \) as the initial \( \Xi_0 \). Taking \( P^{(0)}(t) = \Phi(t)\Xi_0 \) as a nominal control and then linearizing the plant around the approximated equilibrium \( (T_w^*(t), S^*(t), P^*(t)) \), we can get a discrete-time model (3) similar to Eq. (4) which enables us to choose the learning gains \( L_i \) by applying Theorem 1. For convenience, we use \( L_i = K\Xi_0 \) where \( K \) is a constant. Based on the convergence analysis in Section 3, we know that \( K > 0 \).

In practice, one may use some tuning method to schedule different \( K \)'s in different runs which is similar to the PID tuning in the iteration number \( i \)-axis. As the first-order ILC updating law is in fact a pure integral controller along the \( i \)-axis, higher-order ILC scheme may be used which results in a PI or PID controller in the \( i \)-axis. To illustrate this, a second order scheme is used and \( L_2 \) is simply set to be 10\%\(L_1 \). Improved results can be clearly observed in Fig. 1 for both cases: \( K = 20 \) and \( 5 \). It is interesting to note that, when \( K = 20 \), the oscillation has been improved a lot by using a high-order updating law.

Larger \( K \) may result in unacceptable oscillations while smaller \( K \) slows down the convergence as shown in Fig. 1. An “optimal” \( K \) may exist. For example, when \( K \) is set to 10, the terminal iterative learning control gives a perfect tracking after 2–3 iterations as shown in Fig. 2. However, the “optimal” \( K \) is not achievable in practice because the full accurate knowledge about the model is not available. On the other hand, by using the idea of iterative learning, a perfect DT control can still be achieved after several repetitions even when a rough \( K \) is used. Furthermore, in Figs. 1 and 2, the uncertainties have actually been taken into account in the simulation study because a simplified model is used to design the learning gain where the high-order terms are regarded as the modelling uncertainty as remarked in Remark 3. It is shown from Figs. 1 and 2 that the proposed terminal iterative learning control scheme is robust to this uncertainty. As for the disturbance, an additional case is considered where \( v_d(N) \) is set to \( \text{randn}(0.5) \times 0.05 \) \( \mu \text{m} \). \text{rand} is a \text{MATLAB} function to generate a uniformly distributed random noise over \([0,1]\). In this case, the
situation is the same as that of Fig. 1. The simulation results are shown in Fig. 3 where it is clearly observed that the tracking error bound is proportional to 0.025. This is in accordance with the result of Theorem 1. As the RTPCVD system is repetitively operated, the terminal ILC scheme demonstrated above is practically effective.

5. Concluding remarks

The terminal deposition thickness control for rapid thermal process chemical vapor deposition is considered. A terminal iterative learning control scheme with a high-order updating law is proposed. The lamp power control profile is parameterized and the parameters are to be updated by using the terminal DT measurement only at the end of each run. A convergence condition is obtained for uncertain discrete-time time-varying linear systems. Simulation studies on a simplified RTPCVD model show that the desired DT can be achieved by the proposed terminal output learning scheme in a few runs. It is also illustrated that a high order scheme may provide improved convergence performance.

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References


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