15th Triennial World Congress, Barcelona, Spain

OPTIMAL ITERATIVE LEARNING CONTROL OF WAFER TEMPERATURE UNIFORMITY IN RAPID THERMAL PROCESSING

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Abstract: An optimal iterative learning control (ILC) technique based on a quadratic optimal criterion has been implemented and evaluated in an experimental rapid thermal processing (RTP) system fabricating 8-inch silicon wafers. The control technique is based on a time-varying linear state space model which approximates a nonlinear system along a reference trajectory. This ILC control technique is capable of making improvements in the control performance from one run to next and eventually converges to a minimum achievable tracking error despite model error. Through a series of experiments with wafers on which thermocouples are glued, it was observed that the wafer temperatures are steered to the reference trajectory reducing the differences overcoming various disturbances. *Copyright 2002 IFAC*

Keywords: Rapid Thermal Processing, Iterative Learning Control, LQG, time-varying linear state space model, identification

1. INTRODUCTION

Rapid thermal processing (RTP) has emerged as one of indispensable semi-conductor manufacturing processes after a decade of intensive research. The main advantage of RTP over the conventional furnace process is that various wafer manufacturing operations such as annealing, oxidation, nitridation, chemical vapor deposition, and cleaning can be conducted in a single system with reduced thermal budget, enhanced wafer granularity, and cluster compatibility (Roozeboom, 1992). Despite the high promise and wide applicability of RTP, further applications have been deterred by the difficulty in attaining a required level of uniformity in the temperature distribution across the wafer surface. In order to overcome this barrier, research efforts have been made in both the design and control aspects (Badgwell, *et al.*, 1995). As the standard size of the silicon wafer has grown from 6 inches to 8 inches and is now moving to 12 inches, the temperature control requirement will continue to pose new challenges.

In the early stage of RTP system control study, multi-loop PID control had been attempted but found unsatisfactory due to the strong interaction in the system (Dilhac, *et al.*, 1992). After that, the focus was shifted to model-based multivariable control techniques, including model predictive control (Stuber, *et al.*, 1994), linear quadratic gaussian (LQG) control (Gyuhyi, *et al.*, 1992), LQG with an optimally designed feedforward input signal (Cho and Gyugyi, 1997), and internal model control (Theodoropoulou and Zafiriou., 1999),. The performance of a model-based feedback control technique inevitably depends on the quality of the model. Given the fact that various causes such as contamination of the chamber

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wall change the characteristics of an RTP, the performance of the conventional model-based approaches may have limitations unless the model is updated continuously.

As a way to achieve high-performance control while overcoming the modelling demand, iterative learning control (ILC) based on the exploitation of the repetitive nature of RTP operation has been attempted by other researchers (Bien and Xu, 1998; Lee and Lee, 2000). The ILC is a special control technique for batch or repetitive processes that update the current batch operation by feeding back the previous batch information. Chen *et al.*(1997) considered a so-called PI learning rule, which doesn't rely on a process model, and applied it to a single-input single-output (SISO) RTP model. Zafiriou *et al.*(1995a, 1995b) devised a nonlinear model-based run-to-run scheme, which is a direct implementation of a numerical algorithm of optimal control to a real system. They demonstrated the performance with a SISO RTP model. The above approaches are rather preliminary in that they conduct only run-to-run improvement (lacking real-time feedback control) in a deterministic framework. Recently, Lee *et al.* (2001) have proposed an optimal ILC technique, called BLQG (Batch LQG) control, based on a time-varying linear stochastic state space model identified along the reference trajectory. A unique aspect of the technique is that it combines "run-to-run" control with real-time feedback control so that they work in optimal and complementary manner.

In this study, the BLQG technique is implemented in an experimental RTP system processing 8-inch wafers and evaluated its performance. The RTP system has an array of 19 lamps (max. 2Kw each) and three thermocouple measurements across the wafer surface. By partitioning the lamps with three groups, the RTP system was configured as a three-input three-output system. Model identification was conducted using N4SID (Overschee and Moor, 1994) as proposed in Lee *et al* (2001).

2. PROCESS DESCRIPTION

The experimental RTP system used in this study was designed for fabricating 8-inch wafers. The actual apparatus and schematic diagram of the system are shown in Figs. 1 and 2, respectively. The system has 19 linear-type tungsten-halogen lamps (max. 2Kw each) as the heat source. The lamps are grouped into three zones as shown Fig. 2 (seven lamps for the center zone, six lamps for the middle and edge zones, respectively) so that respective lamp zones can exert independent radiation heat on the wafer surface. The wafer is placed on a quartz support and heated in the nitrogen atmosphere. The wafer temperature was measured using K-type thermocouples (TC). In

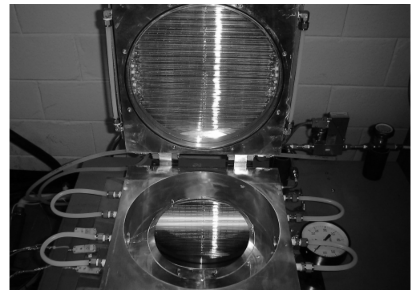

Fig. 1. Picture of the experimental RTP system

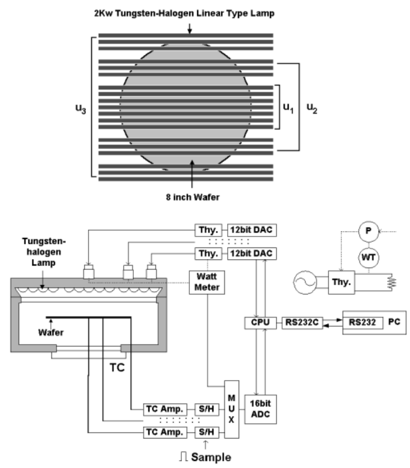

Fig. 2. Tungsten-halogen lamp arrays and RTP temperature control system.

fact, a calibration wafer which has three TC points at the center, middle, and edge of the wafer surface is used as shown in Fig, 2. The system chamber is designed to have embedded coolant paths inside and is cooled by circulating cooling water. As a consequence, the RTP system is configured as a 3x3 MIMO system. Note that there is a special scheme for compensation of the AC power fluctuation. The AC source voltage (220V normally) supplied to the lab can fluctuate by about 10V. This fluctuation poses an unexpected disturbance. Since ILC studied in this research improves the control input on the basis of the input profile of the previous run, such a disturbance at the input may have a harmful effect on the resulting control performance. To compensate the power fluctuation, a kind of AVR is implemented using a high-gain P control.

2.1 *Step Response*

In Fig. 3, a typical step response of the wafer temperatures is shown. The response was obtained around the steady state of 450°C to 5% increase in the lamp power of the edge zone. The responses for other inputs show similar pattern. One can see that considerable effects are given on all three temperatures measurements simultaneously, which demonstrates the high interaction inherent in the system dynamics. An interesting phenomenon is that the response doesn't tend to

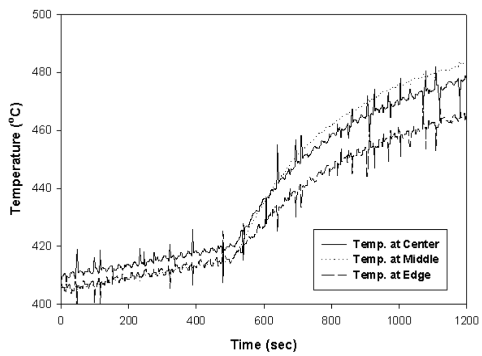

Fig. 3. Step response of wafer temperatures to a step increase of lamp power in the edge zone.

settle at a new steady state easily due to integrating nature. However, such slow dynamics by the large thermal mass of the chamber wall can be easily compensated by feedback control.

2.2 *Experiment Condition*

The overall batch horizon for each experiment was chosen as 30 seconds with the sampling time of 0.2 sec by referring to the dynamic response given in Fig. 4. Also the reference temperature trajectory was as follows:

> *For the first 10 seconds, the wafer is heated from 300°C to 700°C linearly, and then the wafer temperature is maintained at 700°C for the next 20 seconds.*

Cooling trajectory was not considered since the objective of the study is confined to evaluation of a control technique. Also, a higher reference temperature was not attempted by some limitation of the experimental apparatus. Even at 700 °C, a longer operation than 50 seconds induces overheating of cooling water, which may cause leakage and catastrophic damage of the experimental RTP system.

3. MODEL IDENTIFICATION

The optimal ILC (BLQG) technique requires a time-varying linear state space model identified along a reference trajectory. To identify the required time-varying linear state space model, the following steps are taken as proposed in Lee *et al.* (2001):

step 1: Using multi-loop PI control, the wafer temperatures are kept at around 400°C. To the respective steady state input values, independent PRBS's are added for 120 seconds and the resulting temperature responses are taken.

step 2: Both the input and output signals are filtered by

$$f_{filter}(q^{-1}) = \frac{1-q^{-1}}{1-0.925q^{-1}} \quad (1)$$

in order to remove the bias term and high frequency noises. The filtered input and output signals are processed by a subspace identification method, called N4SID (Overschee and Moor, 1994), and a linear time-invariant linear stochastic state space model (valid around 400 °C) of the following form is found.

$$x(t+1) = Ax(t) + Bu(t) + Kv(t), \quad (2)$$
$$y(t) = Cx(t) + v(t), \quad \text{with } R_v \triangleq E\{v(t)v(t)^T\}$$

Here, $u \in R^3$ and $y \in R^3$ rrepresent the lamp power inputs and the temperature measurements, respectively. Also, $x(t)$ and $v(t)$ denote the Kalman state and the innovation.

step 3: Repeat steps 1 and 2 for 600°C. Identification experimental run lasts for 60 sec for this case due to physical limitation.

step 4: Construct a time-varying linear stochastic state space model valid along the reference temperature trajectory after the basis adjustment and model interpolation procedure given in Lee *et al.* (2001). The resulting model has the form of

$$x(t+1) = A(t)x(t) + B(t)u(t) + K(t)v(t), \quad (3)$$
$$y(t) = C(t)x(t) + v(t), \text{with } R_v \triangleq E\{v(t)v(t)^T\}$$

In the above, N4SID employed in step 2 provides a state space model in a balanced form. Due to the balanced realization, a transformed state will be obtained. Hence, a similarity transformation to recover the original is needed in step 4. The idea of model interpolation employed is as follows. Let T_1 and T_2 be two adjacent temperatures and $(\bar{A}_i, \bar{B}_i, \bar{C}_i, \bar{K}_i)$ $i = 1, 2$, be the associated balanced realization. Let T_α be a temperature between T_1 and T_2 such that

$$T_\alpha = (1-\alpha)T_1 + \alpha T_2, \quad 0 \le \alpha \le 1 \quad (4)$$

Since a direct interpolation of the system matrices, would result meaningless model, it is logical to interpolated the frequency gain. Note that the frequency gain from the input to the state is represented by $(e^{j\omega}I - \bar{A})^{-1}\bar{B}$ and that of the dual system is $[\bar{C}(e^{j\omega}I - \bar{A})^{-1}]^T$. Then the system matrices at that linearly interpolate these two gains can be obtained. However, the system matrices suitable for all frequency, $(\bar{A}_i, \bar{B}_i, \bar{C}_i, \bar{K}_i)$, do not exist, and they should be determined in the least squares sense at selected finite frequencies in $\omega \in [0, \pi]$. The detail can be found in Lee *et al.* (2001).

4. OPTIMAL ITERATIVE LEARNING CONTROL

In this section, the optimal ILC technique (BLQG) is briefly reviewed.

4.1 *Stochastic System Model for ILC Design*

In the batch operations, the information on previous runs can be exploited to enhance the control performance for the future runs. Throughout this section, the subscript k represents the run index. In (3), $v_k(t)$ is an *i.i.d.* (independent and identically distributed) sequence during a batch, but $v_k(t)$ for different run indices may show significant correlation. In fact, in terms of k, the error term $v_k(t)$ may exhibit "persistent" or "drifting" behavior in addition to random fluctuations. Such behavior can be reasonably modelled by the equation

$$v_k(t) = \bar{v}_k(t) + \hat{v}_k(t), \quad \bar{v}_k - \bar{v}_{k-1}(t) = n_k(t) \quad (5)$$

where $\hat{v}_k(t)$ and $n_k(t)$ are independent random sequences with respect to both k and t indices. Roughly speaking, $\bar{v}_k(t)$ represents the part of the error that will persist through all future runs while $\hat{v}_k(t)$ is the part that will disappear. Now, (3) can be decomposed into two parts, one that is driven by $u_k(t)$ and $\bar{v}_k(t)$, and the other driven by $\hat{v}_k(t)$.

$$\begin{aligned} \bar{x}_k(t+1) &= A(t)\bar{x}_k(t) + B(t)u_k(t) + K(t)\bar{v}_k(t) \\ \bar{y}_k(t) &= C(t)\bar{x}_k(t) + \bar{v}_k(t) \end{aligned} \quad (6)$$

$$\begin{aligned} \hat{x}_k(t+1) &= A(t)\hat{x}_k(t) + K(t)\hat{v}_k(t) \\ \hat{y}_k(t) &= C(t)\hat{x}_k(t) + \hat{v}_k(t) \end{aligned} \quad (7)$$

Of course, $y_k(t) = \bar{y}_k(t) + \hat{y}_k(t)$. Also, if the reference trajectory for $y_k(t)$ is denoted by $y_d(t)$, the error signal becomes $e_k(t) = y_k(t) - y_d(t)$. In order to put (6) into the standard form in which the external noise is an independent sequence in terms of k as well as t, the difference on the equations for two consecutive runs results

$$\begin{aligned} \Delta\bar{x}_k(t+1) &= A(t)\Delta\bar{x}_k(t) + B(t)\Delta u_k(t) + K(t)n_k(t) \\ \bar{y}_k(t) &= C(t)\Delta\bar{x}_k(t) + \bar{y}_{k-1}(t) + n_k(t) \end{aligned} \quad (8)$$

where $\Delta\bar{x}_k \triangleq \bar{x}_k - \bar{x}_{k-1}$, $\Delta u_k \triangleq u_k - u_{k-1}$. Note that the output equation of (7) can be equivalently written as

$$\begin{aligned} e_k(t) &= C(t)\,\hat{x}_k(t) + C(t)\Delta\bar{x}_k(t) + \bar{e}_{k-1}(t) \quad (9) \\ &+ \hat{v}_k(t) + n_k(t) \end{aligned}$$

where $e_k(t) = \bar{y}_k(t) - \bar{y}_d(t)$. In order to utilize the information on past run, $\bar{e}_{k-1}(t)$ can be included as states. Thus, the following is defined.

$$\bar{\mathbf{e}}_k = [\bar{e}_k(0)^T \ \cdots \ \bar{e}_k(N)^T]^T \quad (10)$$

Now, by including $\bar{e}_k(t)$ in the state while combining (7) and (8), the following augmented state space equation is obtained:

$$\begin{aligned} \begin{bmatrix} \hat{x}_k(t+1) \\ \Delta\bar{x}_k(t+1) \\ \bar{\mathbf{e}}_k(t+1) \end{bmatrix} &= \begin{bmatrix} A(t) & 0 & 0 \\ 0 & A(t) & 0 \\ 0 & \mathbf{C}(t) & I \end{bmatrix} \begin{bmatrix} \hat{x}_k(t) \\ \Delta\bar{x}_k(t) \\ \bar{\mathbf{e}}_k(t) \end{bmatrix} \\ &+ \begin{bmatrix} 0 \\ B(t) \\ 0 \end{bmatrix} \Delta u_k(t) + \begin{bmatrix} K(t)\hat{v}_k(t) \\ K(t)n_k(t) \\ \mathbf{H}^T(t)n_k(t) \end{bmatrix} \end{aligned} \quad (11)$$

$$\begin{aligned} e_k(t) &= \begin{bmatrix} C(t) & C(t) & \mathbf{H}(t) \end{bmatrix} \begin{bmatrix} \hat{x}_k(t) \\ \Delta\bar{x}_k(t) \\ \bar{\mathbf{e}}_k(t) \end{bmatrix} \\ &+ \hat{v}_k(t) + n_k(t) \end{aligned} \quad (12)$$

where, $\mathbf{C}(t) \triangleq \begin{bmatrix} 0 & \cdots & C^T(t) & \cdots & 0 \end{bmatrix}^T$ and $\mathbf{H}(t)$ is a matrix that extracts out the $t+1^{\text{th}}$ element from $\bar{\mathbf{e}}_k(t)$.

4.2 *BLQG Formulation*

The input change $\Delta u_k(t)$ for the k^{th} run is determined according to the following Linear Quadratic Gaussian (LQG) objective subject to (12):

$$\begin{aligned} \min_{\Delta u_k(\cdot)} \ J_k = E\Big\{ e_k^T(N) M e_k(N) + \sum_{t=0}^{N-1} e_k^T(t) Q e_k(t) \\ + \Delta u_k^T(t) R \Delta u_k(t) \Big\} \end{aligned} \quad (13)$$

The above is a standard LQG problem, but the resulting technique will be called as Batch LQG (BLQG) control in accordance with the original motivation of the problem. The optimal solution is standard (Lewis and Syrmos,1995) and given by a combination of the Kalman filter and the Linear Quadratic Regulator (LQR).

4.3 *A Suboptimal BLQG Formulation*

The underlying model (11) for BLQG has a high-order state dimension. Especially, $\bar{y}_{k-1}(t)$ is not measurable and a model for this will contribute to the increase in model size. Hence, it requires a rather heavy computational demand though not too much. In order to enhance the computational efficiency while retaining the basic structure of the underlying model, a suboptimal algorithm is formulated. The key to the suboptimal formulation is to approximate (8) as

$$\begin{aligned} \Delta\bar{x}_k(t+1) &= A(t)\Delta\bar{x}_k(t) + B(t)\Delta u_k(t) + K(t)n_k(t) \\ \bar{y}_k(t) &= C(t)\Delta\bar{x}_k(t) + \bar{y}_{k-1}(t|t) + n_k(t) \end{aligned} \quad (14)$$

Here, $\bar{y}_{k-1}(t)$ is replaced by $\bar{y}_{k-1}(t|t)$ which represents an estimate based on information available at time t of the $k-1^{st}$ run. In this way, the computational burden can be reduced by using readily available information on $\bar{y}_{k-1}(t)$ from the estimated state of the previous run.

By scrutinizing the input calculations, one can see that $u_k(t)$ from suboptimal as well as optimal BLQG control is determined as a summation of the output error over the run index. This run-wise integral action enables us to attain the minimum achievable tracking error as $k \to \infty$ (just as the integral action over time removes steady state offsets) such that

$$J_k \to \min E \left\{ e^T(N)Me(N) + \sum_{t=0}^{N-1} e^T(t)Qe(t) \right\} \quad \text{as} \quad k \to \infty \qquad (15)$$

despite model uncertainty (within certain limits).

5. RESULTS AND DISCUSSION

The identified model obtained at 400 °C is tested for a verification data set which is filtered with (1). Due to the relatively small number of data sets (by the physical limitation of the system), the identified state space model is not accurate but still captures the major dynamics of the system. It has not been tried to elaborate the model further since the BLQG technique possesses a capability to overcome the model uncertainty. The state dimension of 3 was found to be most appropriate for both 400 °C and 600 °C models. Figure 4 exhibits a typical result of BLQG runs. The initial run is conducted with multi-loop PI control, and BLQG control is started based on PI control result. Figures 4(a), (b), (c), (d) show the temperature responses together with the reference trajectory for PI, first run of BLQG, fifth run and then tenth run of BLQG, respectively. It is obvious that the tendency of decreasing tracking error for all three wafer temperatures as the run is repeated. However, result of the tenth run doesn't look improved much compared to that of the fifth run. The theory dictates that, under the situation that there is no random disturbance, BLQG can reduced the squared tracking error to the achievable minimum as the operation is repeated on and on. However, the achievable minimum is determined by the design of an RTP system. Although there is no means to check the achievable minimum tracking error for concerned RTP system and also the temperature measurement is corrupted by persisting random noise, it is thought that the temperature profiles after the tenth run are close to the best attainable ones for the experimental system. More experimental tests are being under way in parallel with improvement from the design aspect (e.g., modification of the lamp grouping, reduction of measurement noise, etc) as well as from the control aspect (e.g., accuracy of the model, etc.). Figure 5 shows the BLQG performance when a disturbance is introduced at

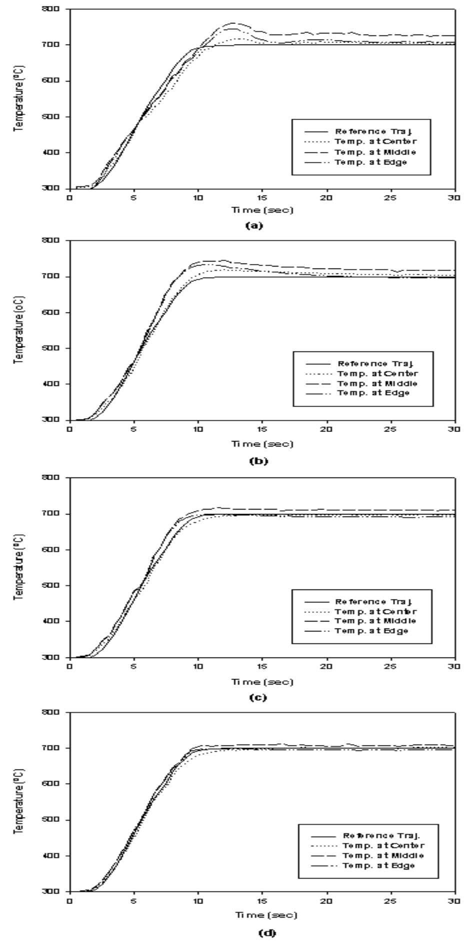

Fig. 4. Response of wafer temperatures (a) with PI control, (b) with BLQG (first run), (c) under BLQG (fifth run), and (d) under BLQG (tenth run).

time 20sec. The disturbance is an injection if cold air. In this result, BLQG could overcome the effect of disturbance as the batch is repeated.

6. CONCLUSION

A computationally efficient linear quadratic gaussian iterative learning control technique, named BLQG, has been applied to a temperature uniformity control of silicon wafers with a prototype RTP system, experimentally. The applied technique conducts run-to-run feedback together with real-time state feedback based on a linear quadratic gaussian criterion. Along with this study, a method for identifying a linear time-varying state space model has also been adopted as an integral part of the control technique.

Experimental application to a prototype 8-inch RTP system shows that BLQG technique performs quite satisfactorily. From the experiment, BLQG technique was found to attain an accurate tracking to the achievable minimum tracking error. Even under a repeated disturbance BLQG

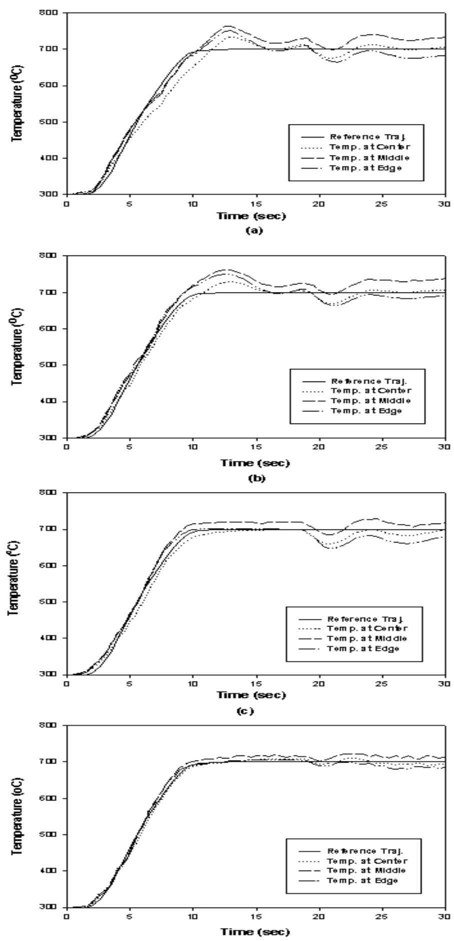

Fig. 5. Response of wafer temperatures of repeated disturbanc occurring (a) with PI control, (b) with BLQG (first run), (c) under BLQG (fifth run), and (d) under BLQG (tenth run).

could compensate the disturbance effect satisfactorily.

7. ACKNOWLEGEMENT

This work was supported by the Korean Ministry of Education through the Brain Korea 21 Project. Authors greatly acknowledge the support from Sangrae Joo, Kornic System Co. for the provision of wafers. J. H. Lee acknowledges the financial support from the National Science Foundation (CTS 9979873).

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