On the Utility of Run to Run Control in Semiconductor Manufacturing*

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Abstract- Run to Run (RTR) control uses data from past process runs to adjust settings for the next run. By making better use of existing in-line metrology and actuation capabilities, RTR control offers the potential of reducing variability in manufacturing with minimal capital cost. In this paper, we survey the types of equipment models that can be used for RTR control, compare existing RTR control algorithms, and discuss issues affecting the potential utility of RTR control.

INTRODUCTION

As integrated circuit producers are driven towards finer linewidths and feature sizes, there is a compelling need for precision manufacture.

In the past, this need has been met by expending considerable effort in the design of processes that are very stable, by isolating environmental effects, and by designing equipment that is insensitive to process drift. Processes are then run with a fixed recipe over batches of several hundred wafers, and occasionally re-tuned by running test wafers.

An alternative approach, and one that is receiving increasing attention, is the use of feedback control techniques to reduce product variability. Preliminary studies have shown that these techniques offer promise for precision manufacture with modest development and ownership cost. Various processes have been studied in this context. See for example Rapid Thermal Processing (RTP) [6], Reactive Ion Etching (RIE) [5], and lithographic sequences [8]. For the next generation of IC technologies with 193 nm lithography, there is a growing consensus that feedback control will prove to be an enabling technology.

Feedback control uses measurements during processing to adjust process recipe settings to correct for process drift. This requires a rudimentary process model, metrology, and actuation capability. In Run-to-Run (RTR) control, recipe settings are adjusted for a given wafer based on metrology from previous wafers. This can use existing in-line metrology, does not require real-time actuation, and is minimally intrusive. For these reasons, RTR control offers the promise of being rapidly integrated into existing fabrication lines and at modest capital cost.

In this paper, we study process modeling, explore various control schemes, and discuss general implementation issues for RTR control as applied to semiconductor manufacturing processes.

MODELS

RTR control strategies require a model of the process and of the disturbances affecting the process. We should like to stress that these models need not be extremely accurate or detailed. Control strategies involve making modest adjustments to input settings to reduce process variability. Therefore, only the first-order sensitivities of the process to input changes are required by the controller. Detailed, accurate models are very important for other problems including equipment and process design.

A nominal process model f relates the process input u to the nominal process output y under idealized conditions (no noise/disturbances) and can be written as

$$y_k^\circ = f(\theta_k, u_k)$$

Here f is parameterized by the process parameters θ. The form of the model f is usually determined from a physical understanding of the process, and the parameters θ are obtained by fitting the model to experimental data. In many situations, the parameters θ represent physical quantities (such as reaction rates or resist parameters) that are not directly measurable. At any rate, the parameters θ may drift from one wafer to the next. We can model this drift as a random walk:

$$\theta_{k+1} = \theta_k + w_k$$

where k is the wafer index, and w_k is a random disturbance, which we will refer to as the *parameter drift*.

We recognize that the nominal process output y° is idealized, and we therefore write the measure process output y as

$$y_k = y_k^\circ + e_k + z_k,$$

* Supported in part by the SRC, the State of California MICRO program, and by AMD, ATMEL, AMAT, LAM, SVG, TI, and NSC.

0-7803-3752-2 /97/$10

where e is the measurement noise, and z is an *offset* drift. Note that, unlike the parameter drift, offset drift simply adds to the output and does not affect input sensitivites.

RTR CONTROL METHODS

RTR control methods fall broadly into two distinct classes: *offset drift cancellation* and *parameter adaptive control* approaches.

Offset Drift Cancellation Approaches

Here process variation is assumed to be entirely in the offset term (i.e. the parameter drift is absent). Consequently, the input sensitivities are assumed to be constant and known. The idea is to estimate the current offset z_k based on past wafer data, and to select the input settings to compensate for the estimated offset.

Exponentially-Weighted Moving Average (EWMA)

This is one of the most intuitive methods [3]. Gradual Mode EWMA assumes a nominal process model of form

$$y_k = Au_k + z_k + e_k$$

It is assumed that the sensitivity matrix A is fixed and that the process variation is entirely accounted for by z_k. An estimate $\hat{z}_k$ for the drift is computed recursively as

$$\hat{z}_k = (1-w)\hat{z}_{k-1} + w(y_{k-1} - Au_{k-1})$$

The choice of w is usually *ad-hoc*, with higher values resulting in more aggressive control. See [4] for a treatment of this subject.

Having obtained an estimate of the drift, the input setting u_k is chosen as the *smallest* adjustment necessary to meet the target T by canceling the estimated drift:

$$T = Au_k + \hat{z}_k.$$

As a compliment to Gradual Mode EWMA, Sachs, et. al., develop a Rapid Mode EWMA Controller [3]. This uses Bayesian decision theory to decide whether or not the plant parameters have changed abruptly, and to then take aggressive corrective action.

The attractiveness of the EWMA scheme lies in its simplicity. The principal difficulties are weight selection and implementation on processes with multiple sensors. EWMA control methods have been successfully deployed on applications such as CMP [7].

Robust Drift Cancellation

This is a novel RTR control approach that like EWMA, assumes a process model of the form

$$y_k = Au_k + z_k + e_k.$$

In robust drift cancellation, the drift is estimated as a weighted average of residuals on a finite window of past data. The advantages of robust drift cancellation are that the weights are explicitly computed from a long history of past process data. Also, an *a priori* estimate of the benefit of RTR control can be determined based on worst-case assumptions of the offset drift statistics.

Suppose we have m lots of process data for lots of L wafers. The design proceeds as follows:

1. Select a window size $n, n << L$

2. For each of the m lots, compute the residual signal $d_k = y_k - Au_k$. We will assume some modeling has been performed to estimate the sensitivity matrix A. Note that d_k includes both the measurement noise and process drift. Compute the correlations

$$R_t = \text{average }(d_k d_{k-t})$$

The values R_t may vary from lot to lot.

3. Find a matrix K, such that for all lots,

$$K > R = \begin{bmatrix} R_0 & R_1 & \cdots & R_{n-1} \\ R_1 & R_0 & \cdots & R_{n-2} \\ \vdots & \vdots & \ddots & \vdots \\ R_{n-1} & R_{n-2} & \cdots & R_0 \end{bmatrix}$$

The matrix K is a measure of the worst case covariance of the residual.

4. Find a row matrix C, such that for all lots,

$$CK^{-1}C^T < LK^{-1}L^T$$

where

$$L = [\ R_1 \ \cdots \ R_n\ ]$$

The matrix C is a measure of the worst-case autocorrelation in the measured residuals.

5. Use any RTR control u satisfying

$$Au_k = -CK^{-1}[\ d_{k-1} \ \cdots \ d_{k-n}\ ]^T$$

6. If there is no parameter drift, and if the process data is representative, then this RTR control scheme will reduce the output variance (per wafer) by

$$CK^{-1}C^T$$

Observe that if there is substantial measurement noise, then L will approximately be zero and the RTR control will disconnect. The advantage of this scheme, is that it robust to statistical assumptions on the offset drift z_k. This is at the expense of using less aggressive control.

Parameter Adaptive Strategies

In this situation, we assume that the observed process drift is due to both parameter and offset drift. The strategy is to "tune" or update the process parameters θ as data becomes available. The input settings are adjusted based on the tuned nominal model and the target output value T.

Kalman Filter Methods

Here, Kalman filtering is used to recursively estimate process parameters θ_k. This requires a linear nominal process model and knowledge of the measurement noise covariance and of the offset drift covariance. These covariances can be estimated from past data.

The equations involved in Kalman filter RTR control methods are somewhat involved: the reader is referred to [1] for details. In [1], these methods were applied to the resist coat process to reduce variability in resist thickness and photoactive compound concentration. Kalman Filter based control techniques have been successfully applied to other processes, such as Reactive Ion Etching [5].

The shortcoming of Kalman filter methods for RTR control in particular, and parameter adaptive control methods in general, is as follows. If there are too many process parameters θ_k, estimating them requires a lot of data. By the time we have enough data to estimate the process parameters, they may have drifted considerably. As a result, the nominal process model is poor and RTR control based on this model can increase process variance. These problems are illustrated in [1].

Statistical Response Surface Approach

In this approach the behavior of the nominal process is described by linear regression models. During the operation of the process, a model-based SPC criterion is used to detect discrepancies between the models and the actual observations. This criterion can be tuned to detect slow, consistent process changes (multivariate, model-based CUSUM or EWMA charts can be used for this). Once a slow, consistent change has been detected, the most recent points are used to update the response surface models using step-wise, principal component regression, and the updated models are then used for estimating the new operational recipe. This technique has been used for feedforward, as well as feedback control [8]. An additional statistical criterion can be used to detect abrupt discontinuities in process behavior (T^2 charts are suitable for this). This can play the role of traditional SQC, where human intervention, or a knowledge based diagnostic system is needed to correct problems [9].

ISSUES

When should RTR Control be deployed?

In semiconductor manufacturing, much effort is made to eliminate sources of variance from manufacturing processes. A natural objection to RTR control is that tweaking process settings between runs adds an unnecessary source of variability. This would only increase the variability in ex-situ wafer characteristics. This objection is indeed true when the process drift is statistically white. However, when the process drift is colored, RTR control can reduce process variance. This is because the drift can be "learned" from past wafer data.

In deciding whether to use RTR control, it is therefore important to check if the process drift is colored. The utility of RTR control increases with greater correlation in the measured drift sequence.

Another common concern is that a RTR control strategy might be too sensitive to measurement noise. Then process setting decisions are made on the basis of spurious data. Measurement noise can indeed be a problem for a RTR controller, but there are ways to mitigate its affects. For example, Kalman Filtering methods explicitly use a model of the measurement noise. A larger measurement noise variance used in the design equations will lead to less aggressive RTR control.

Large measurement noise variances can also be incorporated into an EWMA design, by decreasing the weight w.

Offset Drift Cancellation vs. Parameter Adaptation

It is possible to determine whether or not a process has significant parameter drift by computing cross-correlations between the measured drift d_k and the input settings u_k on a large lot of wafers. If there is little correlation, we can be confident that the offset drift dominates. In this case, we should employ drift cancellation based RTR control.

Offset drift cancellation is a far simpler control strategy in comparison to parameter adaptation. In addition to the benefits of a simpler implementation, the simpler control design offers improved roboustness. This is at the expense of possibly reduced performance. Nevertheless, we believe that offset drift cancellation should be the default choice. Parameter adaptive control methods should be investigated when there is significant parameter drift.

Making a choice between the various available methods for RTR control is a difficult problem. We feel that this is a process dependent issue, and one that should be made on the basis of experiment. It is possible to investigate optimality conditions for various methods, and this can assist the choice of method.

Optimality

If a drift process does indeed have some modest correlation between successive outputs, and/or the measurement noise is significant, then it is important that the RTR controller be carefully optimized.

When the drift obeys a time series stochastic model, it can be shown that the Kalman Filter is optimal. Because of its limited complexity, EWMA methods are optimal for a smaller class of problems. Conditions for the optimality of EWMA can be derived, and moreover, optimal choice of the weight w can be computed based on the variances of the measurement noise and the offset process drift [10].

Stability

The formal analysis of stability in the context of RTR control is difficult, particularly for parameter adaptive control methods. For simple EWMA schemes, stability has been studied in the context of process assumptions [3].

In practice, however, the stability of RTR control is protected by means of hard limits on inputs, and by limiting permissible input changes. In addition, techniques such as "process input SPC" can apply statistical criteria such as the Western Electric Rules to controlled process data to closely monitor the behavior of both the controller and the the process.

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