Estimation and Control in Semiconductor Etch: Practice and Possibilities

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***Abstract*—Semiconductor wafer etching is, to a large extent, an open-loop process with little direct feedback control. Most silicon chip manufacturers rely on the rigorous adherence to a "recipe" for the various etch processes, which have been built up based on considerable historical experience. However, residue buildup and difficulties in achieving consistent preventative maintenance operations lead to drifts and step changes in process characteristics. This paper examines the particular technical difficulties encountered in achieving consistency in the etching of semiconductor wafers and documents the range of estimation and control techniques currently available to address these difficulties. An important feature of such an assessment is the range of measurement options available if closed-loop control is to be achieved.**

***Index Terms*—Closed-loop control, plasma etch, run-to-run control, semiconductor wafer, state estimation, virtual metrology.**

I. Introduction

WITH the continuing drive towards smaller feature sizes [1], there are increased pressures on tolerances in semiconductor wafer processing. As the unit value of wafers increases with these dimension decreases, it is imperative that better quality control be achieved if yield rates are to be maintained. Closed-loop control, and related technologies, are traditionally employed to reduce process variance, with the ability to tightly regulate around process setpoints directly relating to yield. Many of the control issues in semiconductor manufacturing are covered in [2]–[6].

Semiconductor manufacturing processes, such as plasma etch, are highly complex processes, and the minute feature sizes also make etch variable measurement difficult, with measurement feedback a prerequisite for control. In addition, attempts to perform in-situ measurement can disturb the etch process, which is largely run according to a very specific open-loop recipe. Optical and electrical measurement of the wafer provide downstream measurement, which, though not usable for real-time control, could be used in a run-to-run control strategy.

In addition to measurement and control, two associated (and related) areas that can assist in quality improvement are mathematical modelling and virtual metrology. Mathematical modelling involves the determination of a set of mathematical equations to describe the behavior of a process. Such mathematical models are usually embedded in virtual metrology algorithms and also form the basis for model-based control strategies. Virtual metrology (VM) models the relationship between desired unmeasurable variables and other measurable quantities. The model is then employed to "reconstruct" the variables, which are not directly measurable.

This paper is focused on the state-of-the-art in the control and measurement sciences as applied to the semiconductor etch process. It follows the excellent review of Edgar *et al.* [7] (in 2000) and the November 2007 issue of this TRANSACTIONS, which has a Special Section on Advanced Process Control [8]. This paper attempts to present a broad picture of the possibilities in etch control and estimation and presents a sample of the recent literature for illustration. More comprehensive literature listings are contained in [9]–[11].

II. Mathematical Models

The etch process is a multivariable (interacting), nonlinear, distributed parameter process with a significant spread of dynamical time constants. As such, some level of simplification is inevitable if models are to be tractable and computable. Plasma/etch models can be considered at various levels.

- *Particle-in-cell (PIC) models* [12] model the spatial variation in the plasma and, in general, respect the very fastest process dynamics. They are computationally intensive due to the need to compute electric/magnetic fields at mesh points in three dimensions, integration of the equations of motion, and interpolation of the fields to the particle locations.
- *Bulk plasma models,* e.g., [13]–[15], ignore the spatial dimension and focus on the representation of the physical process as a lumped parameter system. While these models are computationally simpler than PIC models, they have no ability to resolve spatial variations, but single point modelled outputs usually focus on specific areas of interest, e.g., ion flux at the wafer surface.
- *Black-box models,* e.g., [16] and [17], largely ignore the underlying physical process and are parameterized from a process behavioral point of view. Measured process inputs and outputs are used to produce a mathematical formula relating outputs to inputs. While black-box models can be used to derive relationships between spatially distributed measurements, they are normally used for bulk or single-point measurements.

Due to an incomplete understanding of plasma physics, it is unlikely that a complete physical plasma model will be achieved. In addition, for some applications, such as model-based control

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and state estimation, models must have the facility to be interrogated in real time. For run-to-run control, computational speed is not so crucial. In general, PIC models [18] are less useful for control due to their computational complexity and the provision of information not crucial to the control problem. In addition, the dynamics of the kinetic reactions, which are accurately modelled by the PIC models, are very fast compared to the dominant (slow dynamics) in etch control loops, which arise primarily from actuator (e.g., throttle valve, gas flow) and sensor dynamics.

At the other end of the spectrum, black-box models [19], including artificial neural networks (ANNs) [17], require the minimum of process knowledge but are only valid for the range of data used to train the models and care needs to be taken in the specification of a parsimonious model structure. Bulk plasma models, based on physical principles, are frequently employed in etch control and can be tuned using process data. For example, a control-oriented plasma model is developed in [20], where a static, multivariable nonlinearity is used to model the plasma, with the (largely scalar) dynamics resulting from sensors and actuators.

Equivalent circuit models are also useful in plasma/etch modelling, particularly where virtual instrumentation relies on impedance measurements [21], and can also be useful in providing corrections to raw radio-frequency (RF) measurements [22].

The challenges and progress in modelling the spatial variation in plasma etch processes are articulated well in Yang *et al.* [23].

III. Measurement and Virtual Metrology

Measurement is vital for process monitoring, diagnosis, and control. Various measurement regimes are possible, including real-time local measurement (e.g., Langmuir probe, optical emission spectra (OES), plasma impedance monitor (PIM), etc.), virtual metrology (to synthesize, in real time, important variables that are not directly measurable), and downstream (delayed) metrology (electrical and optical). The availability of key process variable measurements in real time is crucial to accurate diagnosis and control of plasma etch processes.

A. Diagnostic Measurements

Some measurement devices can provide actual measurement of plasma or etch variables, e.g., the Langmuir probe provides direct measurement of ion flux, while laser inferometry directly measures etch depth. However, the in-situ use of such measurement devices in a production environment can be problematic. Other devices, such as OES and PIMs [24], provide a more indirect measurement of the process variables and can, at least, be used to diagnose the "health" of the process if normal working measurement profiles are known. However, they can also be incorporated in VM strategies to give an indirect measurement of the process variables, e.g., [25].

B. Virtual Metrology

Virtual metrology attempts to provide estimates of quantities that are not directly measurable, based on associated measurements and mathematical models relating the measured and unmeasured quantities. The essential principle of VM, in a semi-

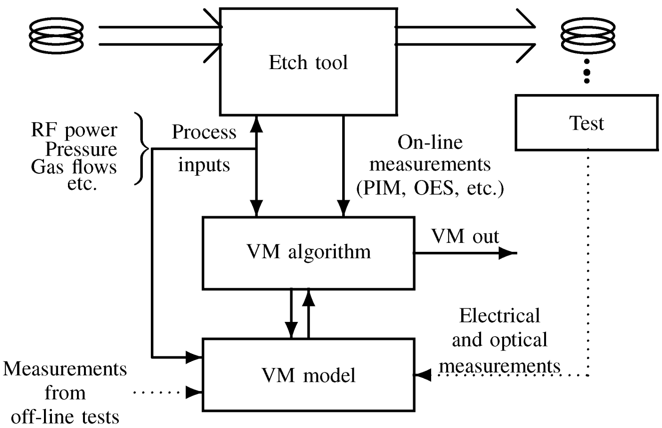

Fig. 1. Virtual metrology principle.

conductor etch setting, is shown in Fig. 1. Known in control parlance as state estimation (dating back to the pioneering work of Kalman [26]), VM can, for some model types (i.e., linear state-space models), provide a predictor/corrector-type structure, as is the case for the Kalman filter [26]

$$\text{Predictor}: \quad \hat{x}_{k+1|k} = A\hat{x}_{k|k} + Bu_k \tag{1}$$

$$\text{Corrector}: \quad \hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_k\tilde{y}_{k+1} \tag{2}$$

where $\hat{x}_{k+1|k}$ is the estimate of the state x using the "open-loop" model (A, B), u is the causal input from which x is derived (e.g., process inputs), $\tilde{y} = y - C\hat{x}$ is the error in the model prediction of a measured variable y $(= Cx)$, and K is the Kalman gain. For the linear (A, B, C) model, K can be determined using an analytical procedure. In contrast to the Kalman filter, most estimation of plasma etch variables is done without a correction term, relying exclusively on the fidelity of the "predictor" model and therefore sensitive to modelling errors and disturbances between u and x.

In general, it is desirable to estimate etch variables, such as etch rate, as regularly spaced samples in time. Endpoint detection is a somewhat special case of virtual metrology, since it focuses more on event, rather than continuous variable, estimation. By way of example, the paper by Lynn *et al.* [27] provides an example of a range of both statistical and neural network modelling paradigms applied for VM to tool variables, with the use of stepwise regression for variable selection.

1) Statistical Analysis: This section documents techniques that use some element of statistical analysis for virtual metrology. Many of the techniques relate to data mining, and some are based on dimensionality reduction [e.g., using principal component analysis (PCA)] and data preprocessing, including pattern analysis. A number of techniques also build mathematical models relating available measurements to key (unmeasurable) etch variables [e.g., partial least squares (PLS)].

The main techniques employed in this category are PCA and PLS. PCA [28] is an unsupervised technique that allows an array of measurements to be concisely described by a reduced number of "principal components," where an attempt is made to explain the majority of the variance in the original measurements using the minimum number of components. The derived principal components are mutually orthogonal and are ordered in terms of amount of variance explained in the original data. Typically, PCA is used to distill information distributed across a number of (potentially correlated) measurements into a smaller number of independent components.

An alternative to PCA, independent component analysis (ICA) [29], can also be used to separate independent signal streams, where the new data basis is formed by a set of independent vectors, rather than orthogonal vectors, as in the case of PCA. Though ICA has found considerable application in areas such as blind source separation [30], the application to semiconductor etch has been limited [31].

Supervised statistical techniques such as PLS and a supervised derivative of PCA, principal component regression (PCR), attempt to derive concise multidimensional relationships between vectors of inputs and outputs. By directing the information distillation activity onto a set of target outputs, PCR and PLS can form the basis of modelling or virtual metrology methodologies. A useful exposure of PCA, PCR, and PLS in a semiconductor etch setting is given in [32].

A variety of measurements have been used to drive VM models. Chen *et al.* [33], for example, developed *chamber state models* of plasma etch using compressed OES data related to etch variables using least squares (LS) on a reactive ion etcher (RIE) with C_2F_6. Data were compressed by manual selection of OES lines, PCA, and partial least squares (PLS) analysis, with model outputs of etch rate uniformity and aspect ratio. In contrast, Tsunami *et al.* [34] used PIM data in a dual-frequency system to estimate etch rate using a simple linear regression model. However, the model has no drift component and loses accuracy over time. Lee and Spanos [35], on the other hand, use process inputs (pressure, power gas flows, etc.) to build a model for RIE process outputs of etch rate, uniformity, selectivity, and anisotropy. Both PCA and PLS returned prediction errors of 7–10%. May *et al.* [36] also used process inputs to estimate etch variables, using response surface modelling. Ragnoli *et al.* [37] compare VM schemes for etch rate using a variety of techniques, including PCR, PLS, forward selection component analysis (FSCA), and forward selection regression (FSR), based on OES data. FSR and FSCA are found to be more effective for feature selection in OES datasets due to the selection of fewer OES lines to summarize key variations in the process data.

Statistical techniques find wide application in fault detection and classification, typically using a data reduction mechanism such as PCA, and sometimes augmented by a modelling tool such as PLS or neural networks. For example, Shadmehr *et al.* [38] found OES to be superior for residual gas analysis (using mass spectrometry) and reported success in predicting thin-film contamination levels. Yue *et al.* [39] also used PCA to detect an etch stop condition in high-density plasma etch. Wise *et al.* [40] compared PCA with other multivariate methods, including parallel factor analysis and trilinear decomposition, for a metal etch fault detection application. Both local and global models were trained with a variety of sensor data, with local models providing the best performance, using machine state signals and RF information. ICA has, in some cases [31], been shown to outperform PCA in fault detection and classification applications, including semiconductor etch. Using a more traditional time-series approach, Guo *et al.* [41] use an ARIMA model to filter real-time signals into identically independent and normally distributed components, followed by the application of Hotelling's T^2 statistic to obtain single scores. The technique was shown to be successful in detecting internal machine variations before wafer product was affected. Forward and reflected powers, in an electron cyclotron resonance (ECR) plasma etch system, were used [42] to aid visualization and fault detection. In particular, forward/reflected power ratios were found to be effective in fault detection and diagnosis. The nonstationarity of etch processes has been directly addressed in [43], where model mean and covariances are adapted during processing, using a version of the exponentially weighted moving average (EWMA) controller. This gave valid operation over six months, including maintenance, cleaning, and new equipment interventions. Summary statistics were also adapted in [44], with a satisfactory Q-statistic over 3000 wafers. Weighted PCA has also been evaluated for use in etch fault detection applications [45].

Endpoint detection is the most popular application of VM, typically using OES measurements, where settings such as integration time can be adapted to optimize signal-to-noise (S/N) ratio and response times [46]. Early applications [47] used a single OES wavelength, but with decreases in open etch area (down to 1%), multiple wavelengths are now employed, usually with PCA processing [48]. For example, Rangan *et al.* [49] used PCA-reduced OES data to form a linear dynamical model, which was shown to be capable of detecting endpoints and transition times in plasma etch. White *et al.* [50], also using PCA with OES data, used the T^2 statistic as a measure of model accuracy (i.e., endpoint detection) and the Q^2 statistic to indicate a need to recompute the PCA basis. Yue *et al.* [51] propose methods to remove uninformative wavelengths from the PCA model by analyzing variance and thresholding PCA loadings. Fifty wavelengths were retained and gave good endpoint detection. More recent work on sparse PCA [52] holds further possibilities for selecting key wavelengths from OES data. Goodlin's Ph.D. dissertation [53] provides a good overview of statistical methods for OES in endpoint detection and devises a method for weighting OES according to S/N ratio.

PIM data can also be useful in endpoint detection, with a number of authors simply using change patterns to indicate the arrival of endpoint [21], [54]. Koh *et al.* [55] applied PCA to the RF harmonics and demonstrated how the loadings changed as the endpoint is reached. Dewan *et al.* [25] developed a PIM phase model, the output of which was compared to measured phase for endpoint detection. PIM-based techniques have also been used to optimize cleaning cycles for chemical vapor deposition processes [56]. In Ragnoli *et al.* [57], nonnegative matrix factorization is employed as a data reduction and variable selection method, where it is applied to OES data for endpoint detection. Results similar to those achieved with PCA were reported.

Imai *et al.* [58] apply PLS-based VM to detect harmful species using dc bias voltage, while a paper by Khan *et al.* [59] uses PLS-based virtual metrology to estimate metrology outputs on a run-to-run, rather then a time-series, basis. Actual metrology values are used to update the PLS model recursively, and the VM scheme and an associated run-to-run controller are applied to a simulated process, with good results.

Some nonlinear derivatives of linear statistical techniques, such as PCA and PLS, have also been employed in VM for etch processes. In [60], a PCA-based support vector machine (SVM) algorithm, which could loosely be described as a kernel PCA method [61], has been employed for endpoint detection, based on OES measurement. The use of an SVM to facilitate nonlinear PLS in a classification/fault detection setting has also been considered [62], though no applications in plasma etch have yet been reported.

2) Neural Networks: Due to their ability to synthesize nonlinear relationships from process data, ANNs have been widely used in virtual metrology for etch processes, finding application in the prediction of etch variables (etch rate, selectivity, anisotropy, etc), fault classification, and endpoint detection.

The work of Kim [17], [63], [64] is representative in demonstrating how etch rate may be determined from manipulated inputs, such as gas flows, power, pressure, and bias, using ANNs. Typically, a static (nondynamical) map between process inputs and actual (offline) measurements is built up and them subsequently used in a real-time way, with typical prediction errors of 5–7% reported [17], [63], [65], [66]. A radial basis function network, as opposed to a multilayer perceptron (MLP), was employed by Kim and Park [67] to model etch rate, based on manipulated inputs. They reported a 40% improvement over some statistical techniques, though Lee and Spanos [35], who compare ANNs to a variety of statistical techniques (LS, PCA, and PLS) could distinguish no improvement, using a wide variety of training signals. Polynomial ANNs were shown by Kim *et al.* to outperform MLPs for etch rate prediction, using chuck gap, RF power, bias, and O_2 fraction as network inputs. ANNs have also been used to produce inverse models for etch rate (i.e., etch rate $\rightarrow$ manipulated inputs), which can be used for real-time control [68]. A paper by Su *et al.* [69] looks at a variety of ANN architectures against the accuracy and real-time requirements of R2R process control. They conclude that recurrent ANNs can satisfy requirements and show application to chemical-mechanical polishing (CMP) and etch processes. The issue of input variable selection for ANN-based VM models is dealt with by Lin *et al.* [70], who use stepwise regression for variable selection from a range of tool variables in an etch process. A similar scheme, using stepwise regression for variable selection with both MLP and radial-basis ANN models, is described in [71] for a chemical vapor deposition process.

ANNs have been employed with OES data, frequently using PCA (or something similar) as a data preprocessing technique. Hong *et al.* [72] compared the use of PCA and ANNs for feature extraction from OES data, with a further ANN used to model the reduced data. However, 226 "relevant" wavelengths are initially chosen from the 2048, prior to compression. The compression ANN returned seven features while PCA returned five, with comparable results for both, giving prediction errors as low as 0.2%. Kim and Kim [73], however, reported a drastic performance improvement with partial OES models (110 wavelengths) compared to conventional PCA-OES reduction.

Selectivity, the ability to etch one material (e.g., Si) at a different rate to another (e.g., photoresist), has also been modelled by ANNs. Himmel and May [65] found ANNs to be superior to quadratic response surfaces, which might be expected since complexity is more limited in the quadratic case. Hong *et al.* [72] compared ANNs and PCA for data reduction in selectivity prediction, concluding that the ANN reduction was significantly better.

Uniformity, a measure of the spatial variation in etch across the wafer, has also been modelled using ANNs, requiring spatial measurements for model building. Lee and Spanos [35] reported little success in modelling uniformity using manipulated variables (gas flows, power, pressure, and gap) as inputs, while Kim and Kim [73] found that the addition of dc bias (as an input) only served to reduce the accuracy and increase the complexity, of the model. However, Kim *et al.* [63] reported a prediction error of just 0.4% using pressure, gas flows, and power as inputs. In the case where OES was used to model nonuniformity alone, PCA was reported [72] to significantly outperform ANN-based data reduction.

ANNs have also been employed to model surface characteristics, such as anisotropy and surface roughness. Hong *et al.* [72] built an ANN model that modelled anisotropy with an error of less then 2%, with Kim *et al.* [63] predicting etch profile angle with an error of less than 4°. However, anisotropy was shown to have a high dependency on RF power. Kim and Kim [73] achieved similar levels of accuracy for etch profile angle, using a reduced set of OES lines, in preference to manipulated inputs, with PCA-OES models also performing poorly. Kim *et al.* [74] successfully produced an ANN model that predicted the discrepancy in sidewall bottom etch rate compared to center etch rate, using genetic algorithms to optimize the spread values. Surface roughness was modelled, using ANNs, in [75] and [67] using generalized regression and radial basis function networks, respectively. Reference [75] also employed GAs for ANN optimization, while statistical models, for the same application, were found to be significantly inferior in [67].

The classification properties of ANNs have been well documented (e.g., [76]), and fault detection and classification for plasma etch is a significant application area. In one of the few applications of a dynamical ANN for semiconductor manufacturing applications, Hong and May [77] apply a time-series ANN for fault identification. The ANN predicts the manipulated inputs (RF power, pressure, and two gas flows) based on the variations in seven OES lines, six atomic mass signals from a residual gas analyzer, and the sample time index. The sample time index gives a measure of the chamber "age" or usage and should help to account for drift due to chamber residue buildup. The system demonstrated a sensitivity to performance deviations down to 10%. In a similar way, though using a static ANN, Shadmehr *et al.* [38] used mass spectometry and OES measurements to predict power and gas flows. The ANN was also able to model thin-film contamination levels on the chamber walls. A dynamical radial-basis function ANN was utilized in [78] to predict manipulated inputs, given a window of previous values. The ANN was trained to incorporate normal

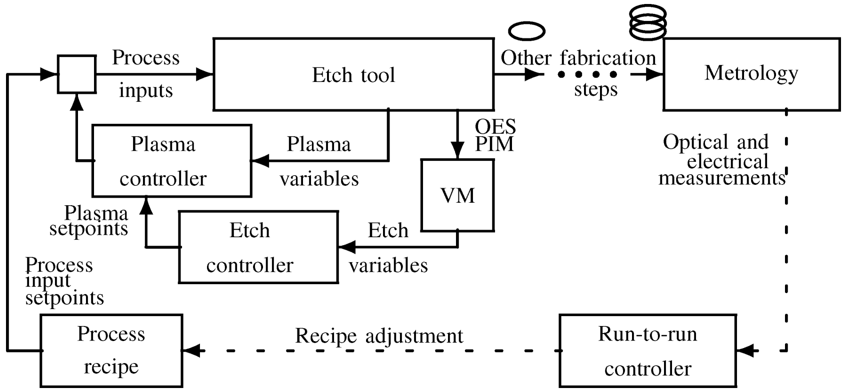

Fig. 2. Etch tool control possibilities.

drift variations and recipe changes and was able to identify abnormal process shifts. A closely related class of paradigm to ANNs, SVMs, which, for certain classes of kernel functions, have a strong similarity with radial basis function neural networks, have also been employed for fault detection, using OES sensor data [79], with 100% success reported for RF faults in an RIE process.

Endpoint detection has also been addressed using ANNs [80]. The ANN is fed with forward and reflected RF power, matchbox capacitor positions, dc bias, wafer plate power, and previous values of these variables, giving a dynamical context to the classifier input. Target training data was provided by expert (manual) indication of endpoint. Results indicated a strong dependence on a change in the RF signals for successful operation. Other ANN applications include the use of a polynomial ANN to predict the dc bias in an etch chamber [81] and the prediction of overetch time required to control residual oxide thickness [82].

IV. Control

The control possibilities for a plasma etch tool are outlined in Fig. 2. From a time-domain perspective, the control structures can be divided into the following two general classes:

1) real-time (discrete-time) control, where measurements are immediately used to adjust the manipulated variables that affect the controlled variable(s);
2) run-to-run control, which uses downstream measurements to adjust setpoints for the next wafer or batch of wafers.

For an etch process, two hierarchical real-time control "loops" are possible, as shown in Fig. 2. Plasma variables, such as ion flux and species concentration, may be controlled using an *inner* loop, where the "recipe" is specified in terms of those quantities and/or an *outer* loop may be employed to control etch variables (such as rate and depth) directly. Both loops however, depend on measurements of the appropriate controlled variables, which can be supplied by sensors or using virtual metrology. The important subject of measurement is dealt with in detail in Section III. For run-ro-run (R2R) control, the immediate provision of measurements is not so crucial, since R2R addresses longer term disturbances, such as residue buildup, etc., and is based on long-term statistical averages.

One must also be mindful of the possible negative impact of the "inner" real-time control loop on the "outer" run-to-run control loop, since the statistical process control (SPC) principles of run-to-run control are based on building up a consistent picture of the statistical process variations. The real-time control normally operates somewhat independently of the run-to-run control, and it is often recommended not to use both approaches simultaneously since, if there is an assignable cause that can be eliminated using SPC, real-time control can mask its effect by making constant adjustments to the manipulated variable. Such masking can, in turn, lead to instability in the process. For more information on this interaction, see [83] and [84].

A. Real-Time Control

Some of the early work on real-time control, sometimes termed engineering process control, for etch processes looks at control variable selection and the design of a multivariable steady-state compensator [85], [86]. Relative gain array and singular value decomposition methods were used to understand the relationship between process variables (i.e., dc bias, species concentration, etc.), etch variables (yield, uniformity, anisotrophy), and manipulated variables (pressure, power, gas flow rates). This permitted the multivariable system to be approximately decoupled using a static 2×2 compensator, with single-input single-output (SISO) controllers used for dynamic control. The issue of variable selection/matching has also been considered by Patterson *et al.* in [87] and [88].

1) Control of Plasma Variables: In this section, the control of plasma variables (such as ion flux and the concentration of various plasma species) is considered, using causal inputs such as RF power, pressure (via valve position), and gas flow rates. In [16], [89], and [90], for example, fluorine concentration $[F]$ and V_{bias} are controlled in real time using power and pressure as manipulated variables. Measurement of $[F]$ was via OES with actinometry, while an inductive tap was used to measure V_{bias}. A 2×2 transfer function matrix for the system was identified and a control algorithm based on linear quadratic Gaussian with loop transfer recovery (LQG/LTR) methods employed. A Hammerstein model component was also added in [91] and [92] to allow static actuator nonlinearities to be accounted for; [92] also addresses the issue of spatial uniformity on the wafer. A control system that regulates the ion energy (measured using a Langmuir probe) in a capacitively coupled RIE is reported in [93].

V_{bias} was adjusted using a resistor in parallel with the blocking capacitor. It was deliberately chosen not to use RF power and gas concentrations as control variables, since these affect other aspects of the etch. Two applications, selectivity enhancement and ion-enhanced plasma cleaning, were shown to benefit from the control, though a reduction in plasma stability was noted. A slightly different approach is presented in [94], where ion current and ion energy are controlled via RF power and bias power using two SISO PI controllers. Ion current is estimated from antenna impedance, while ion energy is inferred from root mean square RF voltage. A decoupling compensator, controlling ion flux and species concentration in a variety of $Ar/O_2/C_4F_8$ plasmas, is presented in [95]. In particular, the multivariable interaction between the manipulated variables (RF power, gas flows) is addressed. More recently, Lin *et al.* [96] describe a scheme where RF power is manipulated to control electron density and ion energy, where a transmission line microstrip microwave inferometer is used to measure electron density. This scheme is shown to achieve good consistency in etch characteristics and can counteract the "first wafer" effect. A fuzzy logic controller was shown to outperform a traditional PI controller.

Hanish *et al.* [97] demonstrate one of the few applications of an asymptotic observer, an extended Kalman filter (EKF), which is used to estimate $[Cl]$ from OES with actinometry. Two SISO PID controllers are used to control $[Cl]$ and pressure, using the rate constant of dissociation and "gas loss" (essentially outlet flow plus gas loss to chamber walls) as manipulated variables. A PID controller is also employed by Klimecky *et al.* [98] to control plasma density, using RF power as a manipulated variable. One of the significant features is the claim that the controller can compensate for transient chamber wall conditions and therefore provide better consistency in the face of residue buildup.

2) Control of Etch Variables: In this section, the control of etch variables, either directly or indirectly, is considered. An interesting paper by Vincent *et al.* [99] employs an EKF to measure etch rate, using dual-frequency reflectometry as a correcting output. The focus is on the use of power, as a manipulated variable, to control etch rate, using a PI controller, though other control structures could be considered. The authors report an 83% improvement in etch depth results compared to a purely timed etch. A model-based feedback controller is reported in [68] and [100], controlling etch rate, which is measured using laser inferometry and a profilometer. Manipulated variables are pressure, RF power, and gas flow, and a linear LQG/LTR controller is compared to a nonlinear adaptive controller based on a neural network model. The nonlinear adaptive controller is shown to be superior under parameter variation and disturbance conditions. Armaou *et al.* [101] describe a PI-based control scheme that manipulates gas flows to control three spatially distributed measurements of etch rate. Results are presented for a simulation and demonstrate a potential reduction in etch-rate nonuniformity from 30.2% to 3.8%.

In [102], the control system is extended to include the control of V_{bias}. Etch rate of GaAs, measured using spectroscopic ellipsometry, is also controlled in [103]. A model-based LQG controller is used to manipulate pressure, where the model is determined by fitting experimental data to a first-principles structure. This paper also presents a robust adaptive controller for a Si_3N_4 etch application based on an empirical model. The use of phase difference between upper and lower RF signals as a manipulated input acting on etch characteristics has been demonstrated by Sung *et al.* [104] and could provide the basis for real-time control.

B. Run-to-Run Control

In contrast to real-time control, R2R control works with delayed measurements and is driven by the availability of wafer measurements. It therefore falls into the class of *discrete-event* rather then *discrete-time* (as is the case of real-time control) systems. An excellent overview of the application of R2R control in the semiconductor industry is given in the book by Moyne *et al.* [105]. R2R control has its origins in SPC, which provides tools for the detection of process faults using statistical techniques. R2R extends these ideas to provide active control via feedback.

1) Algorithms: Since there are a small number of R2R algorithms, mostly based around the EWMA controller [84], we give the SISO double EWMA controller (which can cater for both slow drifts *and* fast shocks) [106] as

$$Y_t = a + bX_{t-1} + d \cdot t + \varepsilon_t \tag{3}$$

$$\hat{a}_t = \lambda_1(Y_t - bX_{t-1}) + (1-\lambda_1)\hat{a}_{t-1} \tag{4}$$

$$\hat{d}_t = \lambda_2(Y_t - bX_{t-1} - \hat{a}_{t-1}) + (1-\lambda_2)\hat{d}_{t-1}$$
$$0 < \lambda_1, \lambda_2 \le 1 \tag{5}$$

$$X_t = \frac{\bar{Y} - \hat{a}_t - \hat{d}_t}{\hat{b}} \tag{6}$$

where (3) defines the process model, (4) and (5) are estimators for the model parameter and drift, respectively, with (6) calculating the manipulated value. Y_t is the controlled variable (e.g., etch depth), $\bar{Y}$ is the setpoint for Y_t, X_t is the manipulated variable, a and b (which is determined a priori) are model parameters, and ε_t is a disturbance. The "^" notation is used to denote an estimate, and λ_1 and λ_2 are tuning parameters used to specify the sensitivity to variations in a_t and d_t, respectively. The choice of λ_1 and λ_2 is discussed in [84]. Note that the double EWMA controller assumes a linear drift in the process, of the form $d \cdot t$, and implements a form of deadbeat control [107], which attempts to regulate the process output in minimum time (samples).

Since EWMA controllers are based on statistical measures of process behavior, their use with mixed products needs to be considered carefully. One solution to the mixed product problem include the employment of a disturbance model for $\hat{d}_t(i)$ for each product type i, with the appropriate $\hat{d}_t(i)$ used in the deadbeat control calculation in X_t [108], [109]. EWMA controllers can also be used across different tools, via the use of multiple process models [108], by employing different a and b parameters for each tool. Zheng *et al.* [108] also consider the stability and performance implications of using multiple process and disturbance models.

2) Model Identification: While (4) provides an estimate for a, Wang *et al.* [110] prefer a Bayesian statistic for the detection and classification of disturbances in order to obtain better parameter estimation and illustrate its use on a film deposition process. An additional common method for parameter estimation of linear models is least squares (LS), frequently used also in R2R control [111]–[115] (simulated CMP process). In this case, (3) is replaced by a recursive LS estimator for the online estimation of the intercept a, while a weighted LS algorithm [116] allows the assignment of preference to current measurements versus past measurements. Palmer *et al.* [117] employ a Kalman filter to estimate both the gain and the intercept and apply it to a photoresist deposition process. The "age-based" double EWMA controller presented in [118] introduces a term into the model to represent a drift due to the tools' wearing, which is proportional to the number of runs since the last maintenance operation.

3) Weight Determination: The performances of EWMA-type controllers are strongly affected by the choice of the weights λ_1 and λ_2 (also called "forgetting factors") [84], [119]. Discussion and methods concerning the optimal choice of weights can be found in [120] (CMP application), [121], and [114], while in [122], the choice of the weights is studied with respect to the performance tradeoff between the short-term and long-term responses of the system. In [123], weight optimization trades off controlled variable regulation against manipulated variable effort, using a heuristic algorithm. A similar strategy has been adopted in [124], where the minimization focuses on the regulated outputs, using dynamic programming theory. In [125], a neural network is used to map the relation between the disturbance state (drift and noise) and the optimal weight of an EWMA estimator.

4) Multivariable Models: Modifications to the basic EWMA controller, with etch applications, include extensions to allow multivariable models [84], nonsquare models [105], and nonlinear models [114]. With regard to nonsquare systems, there are two possibilities:

a) more output (controlled) variables than available manipulated variables (underactuated);
b) more manipulated variables than outputs (overactuated).

In the case of a), a "best compromise" solution can be achieved using least squares type solutions (see [105]). One possibility is also to attach a greater importance to the regulation of one or more controlled variables, as exemplified for the chemical-mechanical polishing (CMP) case in [126]. In the overactuated case, some additional freedom is available to the control designer, over and above regulating the controlled variables. One way to exploit this freedom, seen in a variety of control applications, is to minimize the energy or variance of the control action. This is vital in some applications, such as aerospace, where limited energy to power actuators is available, but could also encourage less actuator wear and material usage in semiconductor etch. Examples of how overactuated systems are dealt with include:

- weight assignment to minimize the variance of specific manipulated variables (for a CMP process) [120];
- the use of Lagrange multipliers for new recipe calculation (silicon epitaxy and CMP applications) [121];
- the use of a nonsquare matrix pseudoinverse (which can be related to least squares minimization of the manipulated variables) [119];
- the use of PLS to determine a diagonalizing (nonsquare) precompensator, followed by application of multiple single-loop double EWMA controllers [127] (also for a CMP application);
- ridge regression [128], where a bound is put on manipulated signal values.

The paper by Khan *et al.* [59] uses a multivariable EWMA controller based on a PLS model in both wafer-to-wafer and lot-to-lot control, where an advantage in wafer-to-wafer control is highlighted.

Bounding the manipulated input signal, in addition to potentially reducing actuator wear and energy use, also has the advantage of respecting actuator constraints (both amplitude and rate), reducing the incidence of nonlinear behavior. In addition to the input bounding method of Rajagopal and del Castillo [128], Boning *et al.* proposed the recursive bound pinning technique [120] (demonstrated on a CMP application).

5) Nonlinear Models: Nonlinear models give the possibility of obtaining a better description of the process, which can subsequently improve the R2R control performance. Using static (nondynamical) polynomial elements, it is possible to introduce nonlinearity in the model while retaining the ability to employ recursive LS estimation techniques, as in [115], [114], and [111], since the model is still linear in the parameters. A second-order polynomial is employed in [106] and [112], where the estimation technique is based on a steady-state design of experiments (DOE). A different approach has been taken in [129], where a bounding ellipsoid algorithm is employed to estimate parameters of a second-order polynomial model. At each iteration, the algorithm returns an outer bounding ellipsoid of the likely process parameter set. Ramaswamy *et al.* [130] designed a variable gain controller for the compensation of nonlinearities, which solves a min-max problem to find the input adjustment that minimizes the worst case predicted error using a double EWMA controller.

Neural networks are also widely used due to their ability to model nonlinear systems; however, a large number of samples are generally required for training. This is not a substantial issue in high-volume manufacturing, such as semiconductor etch, since most production plants are equipped with extensive databases for the recording of large numbers of process variables. Such data have been used in [82], [123], and [131]–[133] to train a neural network for the mapping of etch process input/output relationships. A neural network model, predicting etch rate, is combined with a real-time optimizer in [131] to provide process setpoints to alleviate long-term process drift and sensitivity to PM interventions. The ANN model is trained with extensive historical process data prior to use. By comparison, in [91] and [134], the data for the training of the neural network are collected by performing a specific experiment using DOE techniques.

6) Other R2R Control Structures: Though EWMA controllers are among the most popular in semiconductor process control, a number of other structures have been investigated. Controllers based on *disturbance feedforward* adjust the recipe in accordance with the outcome of upstream processes, with etch applications reported in [135] and [136]. Another type of "lookup" controller interrogates historical data to look for a similar previous situation or interpolates to find the closest match [137]. Both of these controller types provide more conservative options than R2R algorithms, which allow batch-to-batch adjustment and are common in many production environments.

Using intelligent systems methods, fuzzy logic and database learning have been incorporated into a generic R2R etch controller in [138], while genetic algorithms for recipe generation and low variance control have been used in [139] and [140]. A multiresolution reinforcement learning approach to R2R control was also examined in [141].

Model predictive control, which has found widespread application in real-time process control, has also been extended to R2R control in [142] and [143], while Hamby *et al.* [144] adopted a probabilistic approach to R2R control.

A number of other issues relating to R2R control, such as stability, robustness, and measurement delay, are also important and have received some attention in the published literature but are omitted here for brevity. The interested reader is directed to [10] for an overview.

V. Conclusion

Since plasma etch in semiconductor processing is such a high-value process, it has attracted significant attention in attempts to improve the process quality and consistency. However, in most production environments, such processes are effectively run in "open-loop" mode, with reliance on consistency in recipe and etch chamber state. In some instances, some schedule-based correction to the recipe is applied to account for process drift due to residue deposition on the chamber walls. While a number of run-to-run applications are reported, particularly in experimental setups, there is a paucity of documented application of real-time control of process variables. The principal reason for this is that direct measurement of key etch variables is difficult (Langmuir probes are invasive, while reflectometry is notoriously difficult in a production environment), with virtual metrology providing a promising alternative, using indirect measurements (such as OES and PIM) as a basis. However, most current VM strategies use only a forward model, unlike the predictor-corrector structure, which is characteristic of linear state estimators. This could provide a possibility for improvement of VM algorithms. With the availability of reliable measurements, there is an enormous range of control algorithms that could be brought to bear [145], [146]. Predictive control, for example, has many desirable characteristics and has been widely applied in industrial process control settings [147].

One real-time control possibility is to attempt to directly control plasma variables, such as ion flux and species density, and to base a "recipe" on these variables, which may help to achieve consistency in etch, in an environment experiencing drift (residue buildup) and step changes (PM steps). Run-to-run control for etch still has a number of important challenges, some of which arise from the delay and others related to the uncertainty associated with the effect of other processing steps between actuation and measurement. The delay may result in significant product wastage before corrective action is taken and provides a stability challenge for the control engineer, while the presence of intermediate process steps between actuation and measurement creates a difficulty in relating effect to cause. However, run-to-run control algorithms appear to have mainly converged to variants of the EWMA type.

The selection of key variables is an important issue. Indirect measurements, such as PIM and OES signals, are high in dimension, and appropriate dimension reduction is vital if etch variables (such as etch rate) are to be reconstructed using virtual metrology. Likewise, selection of key manipulated variables is important since the plasma etch process is a highly interactive multivariable nonlinear system and care must be taken that only the desired controlled variables will be affected by feedback control action.

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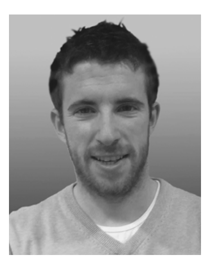

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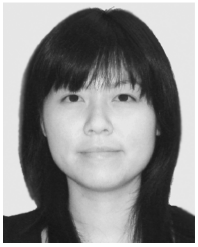

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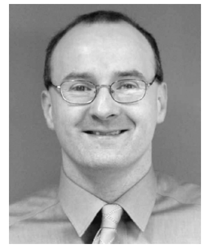

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