Empirical analysis of metrological data fusion for dose control on nano scale lithography

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ABSTRACT

The shrinking CD into nano scale demands more accurate and stable dose control. Recently, the immersion lithography has added extra disturbing factors, such as bubbles, particles which directly impact on current in-line metrology and dose control performance. We present a methodology to characterize the dose metrological data and control approach to secure the metrological fidelity for accurate and stable dose control. First, the time sequence and power spectral domain analysis generate the statistical tendency which shows the confidence area of metrological feedbacks. Then, the 2^{nd} order data fusion from both in-situ and in-line metrological channels is employed to generate a statistical significance of critical external perturbations. Thereafter, an Extended Kalman Filter (EKM) is implemented to integrate to a knowledge based autonomous calibration controller. The controller design is verified successfully to remove the critical external perturbation and to predict the next metrological calibration timing.

Keywords: immersion lithography, dose control, metrology, data fusion, Extended Kalman filter

1 INTRODUCTION

In nanoelectronic production, optical lithography has extended to 65nm and soon will be a 45nm node on VLSI patterning. Experience shows that dose and focus depth are the main factors for usable process latitude on lithography process. With the shrinking critical dimension, more accurate and stable dose control [1] is required to keep the process in a good yield window. In order to achieve this goal, a delicate feedback mechanism for dose control in real time is essential. However, current litho tool lacks the technology needed to detect the accumulated dose level on wafer surface during pattern exposures. Therefore, extra periodical calibrations are required to align different channels of metrological feedbacks. Recently, the immersion lithography has added an extra disturbing factor to the process, from bubbles and particles (Fig.1) which directly impact current in-line metrology and dose control performance. Several works [2, 3] have reported the potential bubble effect on imaging distortion and process latitude shrink in various scenarios. Various random defects processes and even lengthy yield ramp up can be induced by the presence of bubbles. In order to minimize random defects and speed up process optimization, a more robust dose control mechanism in immersion lithography process has to be addressed. This motivates the present study.

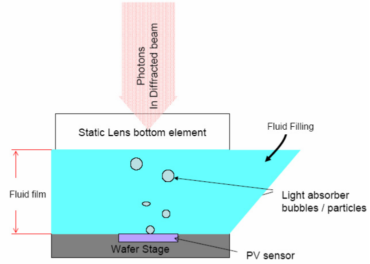

Fig 1 Scenario in immersion lithography

In the Kohler illumination system, there are two photovoltaic sensors in the light path. One is located in the light path and takes the in-situ split light measurement. The other is an in-line sensor, located on the wafer stage corner and is used for specific sensor calibration or optics performance qualification. Under this metrological configuration, the dynamic performance of dose level control on the wafer relies on the real time feedback of the in-situ sensor and proper periodical calibrations of the in-line sensor. In the production environment, the in-situ and in-line sensors provide the feedbacks for dose stability. The exposure latitude calibration through focal exposure matrix on wafer is a common practice. The in-situ sensor provide 8 levels of power density to explore the power spectral response of the measurement and the in-line sensor generates the synchronized measurement that can be used for the measurement variation reference.

2 DESIGN OF EXPERIMENT AND DATA ANALYSIS OF METROLOGICAL PERFORMANCE

The 8 levels of power spectral response data and the difference between the in-line and the in-situ sensor are collected to explore the suspected micro bubble effect. First, in time domain, we explore the measurement variation and repeatability in 13 sampled time sequence with 8 levels of power density. The averaged measurement variation shows the non-unique behavior between different power density levels with respect to time (Fig.2). The averaged measurement repeatability reveals significant variation in low power density levels (Fig.3). Second, we explore the correlation between measurement variance and repeatability under different power density levels. The result shows both power spectral and time series domains suffer from measurement disturbance and their correlation also varies with different power density levels (Fig.4). Through a regression analysis, the metrological tendencies of various test results (Fig.5) are identified. The tendency shows that the confidence area of metrological feedbacks selection should lie on the conjunction of variance, repeatability, time sequence and power spectral domain. Typically, the probability of measured variance is Gaussian, implying that the next measurement result's location is correlated with the previous measured variance and shows Gaussian distribution in the noise band. The probability of bubble effect on the measurement is non-Gaussian. This implies that the measured "surge" or "disturbance" occurs randomly. In order to consolidate the feedback data and extract meaningful significance without scarifying the original measured data, we further fuse the derivative 2nd order of variance and repeatability data from both in-situ and in-line sensors and generate a statistical significance of the critical external perturbation (Fig.6). This external perturbation is most likely due to random bubble effect in measurements and has to be removed before being misused for feedback control.

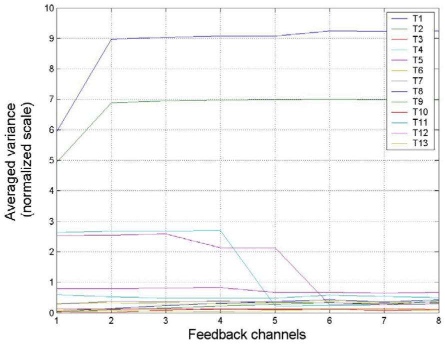

Fig.2 Measured variance in time domain

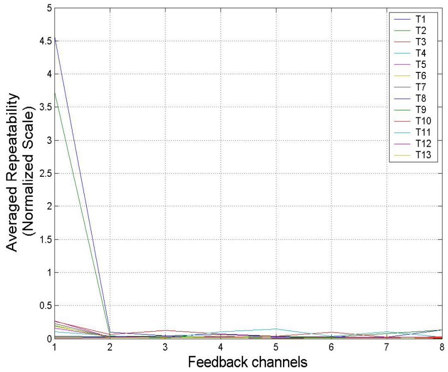

Fig.3 Measured repeatability in time domain

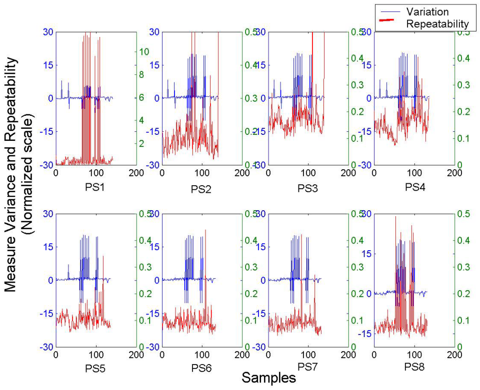

Fig.4 Measured Power Spectral domain trend of variance and repeatability propagation

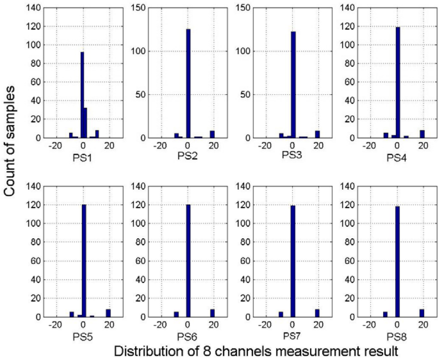

Fig.5 Measured Power Spectral domain distribution tendency

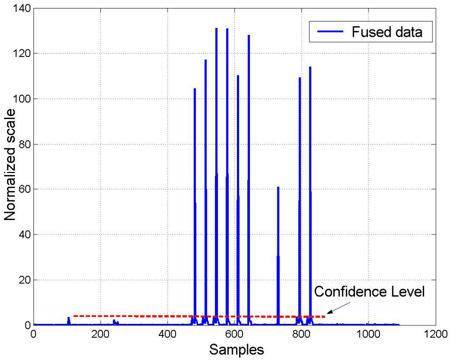

Fig.6 Statistical significance extracted from 2nd order fused data

In order not to remove the data that represent potential sensor drifting from aging, the filter design has to depend on the confidence level and confident area of the calibration period.

3 PROCESS MODELING AND CONTROL IMPROVEMENT

It is noted that the timing for sensor calibration depends on two scenarios: (1) the sensed data show a consistent drifting or offset that is out of control limit; (2) the variation between in-situ and in-line sensors shows contradictive behavior and can be examined by its 1st order and 2nd order fused data. The timing can be weekly in periodical maintenance while the 2nd order fused data showing longer term smooth drifting. The decision has to base on the knowledge through several batches of observation.

To improve the dose control reliability and trigger the action automatically, an autonomous calibration controller is proposed (Fig.7).

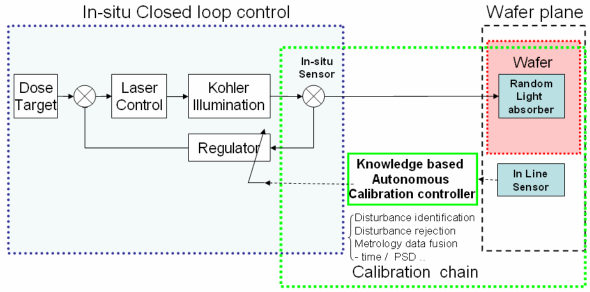

Fig.7 Autonomous calibration controller

To deal with the discrete feedback system, we use the state space approach to handle the multivariate data and the nonlinear, non-Gaussian process. To deploy a statistical modeling of the system and noise behavior, we consider the evolution of the state sequence $\{X_k, k \in N\}$ of a dose target as given by

$$X_k = f_k\left(X_{k-1}, V_{k-1}\right) \tag{1}$$

Where $f_k : \Re^{n_x} \times \Re^{n_n} \rightarrow \Re^{n_z}$ is a nonlinear function of the state, $X_{k-1}, \left(V_{k-1}, k \in N\right)$ is a process with noise sequence and n_z, n_n are dimensions of the state and process noise vectors respectively, and N is the set of natural numbers. The object of tracking is to recursively estimate X_k from measurement

$$Z_k = h_k\left(X_k, n_k\right) \tag{2}$$

where $h_k : \Re^{n_x} \times \Re^{n_n} \rightarrow \Re^{n_z}$ is a nonlinear function and $n_k, k \in N$ is a measurement noise sequence. In particular, we seek filtered estimates of X_k based on the set of all available measurements from time sequence 1 up to sequence k and denoted as $Z_{1:k} = \left(Z_i, i = 1,\ldots,k\right)$. From a Bayesian perspective, the tracking problem is to recursively calculate some degree of belief in the state X_k at time sequence k .from given data $Z_{1:k} = \left(Z_i, i = 1,\ldots,k\right)$. Thus, it is required to construct the probability density function (pdf) $p\left(X_0 \middle| Z_0\right) \equiv p\left(X_0\right)$ of the state vector, which is also known beforehand. Then, in principle, the pdf $p\left(X_k \middle| Z_{1:k}\right)$ may be obtained, recursively, in two stages; namely prediction and updating. Suppose the required pdf $p\left(X_{k-1} \middle| Z_{1:k-1}\right)$ at time $k-1$ is available. The prediction stage involves using the system model to obtain the pdf of the state at time sequence k via the Chapman-Kolmogorov equation as follows:

$$p\left(X_k \middle| Z_{1:k-1}\right) = \int p\left(X_k \middle| X_{k-1}\right) p\left(X_{k-1} \middle| Z_{1:k-1}\right) dX_{k-1} \tag{3}$$

Note that in (3), use has been made of the facts that $p\left(X_k X_{k-1}, \middle| Z_{1:k-1}\right) = p\left(X_k \middle| X_{k-1}\right)$ as (1) describes a Markov process of order one. The probabilistic model of the state evolution $p\left(X_k \middle| X_{k-1}\right)$ is defined by system equation (1) and the known statistics of V_{k-1}. At time sequence k, a measurement Z_k becomes available, and may be used to update the prior state via Bayes rule.

$$p\left(X_k \middle| Z_{1:k}\right) = \frac{p\left(Z_k \middle| X_k\right) p\left(X_k \middle| Z_{1:k-1}\right)}{p\left(Z_k \middle| Z_{1:k-1}\right)} \tag{4}$$

Where the normalized constant

$$p\left(Z_k \middle| Z_{1:k-1}\right) = \int p\left(Z_k \middle| X_k\right) p\left(X_k \middle| Z_{1:k-1}\right) dX_k \tag{5}$$

depends on the likehood function $p\left(Z_k \middle| X_k\right)$ defined by the measurement model of equation (2) and the known statistics on N_k. In the updating stage (4), the measurement Z_k is used to modify the prior probability density to obtain the required posterior probability density of the current state. The recurrence relations (3) and (4) form the basis for the optimal Bayesian solution.

4 OPTIMAL DESIGN BY EXTENDED KALMAN FILTER

To treat the local nonlinearity of the noise behavior, an Extended Kalman Filter (EKF) [4] is used. Assume the posterior density at every time step can be approximated as Gaussian. Then, parameterized by mean and covariance, models (1) and (2) can be rewritten as,

$$X_k = f_k X_{k-1} + V_{k-1} \tag{6}$$

$$Z_k = h_k X_k + n_k \tag{7}$$

The functions f_k and h_k are known matrices defining the linear function. The covariance of v_{k-1} is Q_{k-1}, and the covariance of n_k is n_k. We consider the case when v_{k-1} and n_k have zero means and are statistically independent. The EKF based on $p\left(X_k \middle| Z_{1:k}\right)$ is approximated by a Gaussian as

$$p\left(X_{k-1}\middle|Z_{1:k-1}\right) \approx N\left(X_{k-1}; m_{k-1|k-1}, p_{k-1|k-1}\right) \tag{8}$$

$$p\left(X_{k}\middle|Z_{1:k-1}\right) \approx N\left(X_{k-1}; m_{k|k-1}, p_{k|k-1}\right) \tag{9}$$

$$p\left(X_{k}\middle|Z_{1:k}\right) \approx N\left(X_{k-1}; m_{k|k}, p_{k|k}\right) \tag{10}$$

Where

$$m_{k|k-1} = f_k\left(m_{k-1|k-1}\right) \tag{11}$$

$$P_{k|k-1} = Q_{k-1} + \hat{F}_k P_{k-1|k-1} \hat{F}_k^{\,T} \tag{12}$$

$$m_{k|k} = m_{k|k-1} + K_k\left(Z_k - h_k\left(m_{k|k-1}\right)\right) \tag{13}$$

$$P_{k|k} = P_{k|k-1} + K_k \hat{H}_k P_{k|k-1} \tag{14}$$

Note that $f_k(.)$ and $h_k(.)$ now are nonlinear functions, and $\hat{F}_k$ and $\hat{H}_k$ are localizations of these functions as follows:

$$\hat{F}_k = \frac{df_k(x)}{dx}\,;\; x = m_{k-1|k-1} \tag{15}$$

$$\hat{H}_k = \frac{dh_k(x)}{dx}\,;\; x = m_{k|k-1} \tag{16}$$

$$S_k = H_k P_{k|k-1} \hat{H}_k^{\,T} + R_k \tag{17}$$

$$K_k = P_{k|k-1} \hat{H}_k^{\,T} S_k^{\,-1} \tag{18}$$

5 DESIGN VALIDATION

We examine the EKF filter design for the modeled process on two goals: (1) to verify if the filtered data can result in a Gaussian distribution; (2) to verify the filtered data still retain the representation of long term drifting behavior. The result denoting the first goal is shown in Fig.8. It indicates a successful approximation of Gaussian in distribution after filtration of the noised data. This is related to measurement system behavior without significant random disturbance. Then, based on this process behavior, we further investigate if the behavior can be predicted in longer term for calibration purpose. For the metrological process drifting prediction, a polynomial fitting is used on the filtered data and the result is depicted in Fig.9. The result shows this metrological process being slow drifting, which is crucial from natural aging of the sensors. This predicted trend also suggests a calibration timing on when the dose control limit is about to be out of range. In this case, a recursive of two-week measurement data suggests a four-week calibration period be necessary. By implementing this behavior into the autonomous calibration controller, the auto calibration can be achieved.

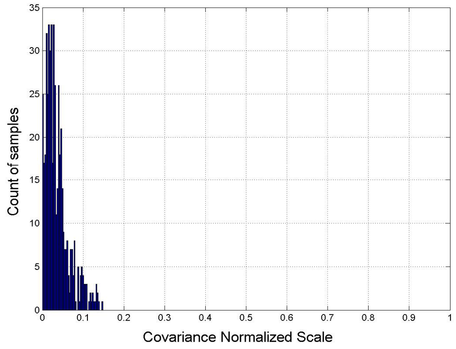

Fig.8 EKF filtered data distribution

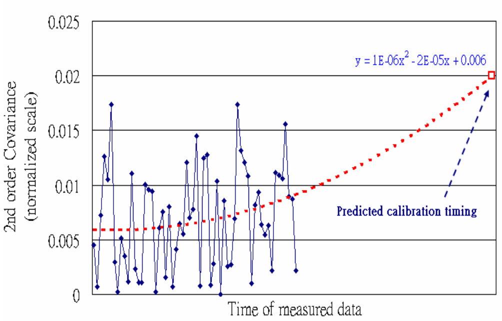

Fig.9 Predicted measurement process performance for calibration timing

6 CONCLUSIONS

We present a methodology to characterize dose metrological data with errors most likely coming from bubble effect in the immersion scenario. The Extended Kalman Filter (EKF) is used to extract masked information to construct a knowledge based autonomous calibration controller. This controller is successfully validated to optimize tool metrological calibration cycles and retain metrological fidelity.

Reference

[1] S.Postnikov, S.Hector, C.Garza, R.Peters, V.Ivin, “Critical dimension control in optical lithography” , J. of Microelectronic engineering. vol 69, 2003, p452-458
[2] B.W.Smith, A.Bourov, H.Kang, F.Cropanese, Y.Fan, N.Lafferty, L.Zavyalovy, “Water immersion optical lithography at 193nm”, J. Microlithography, Microfabraction and Microsystem. 3(1), 44-51, 2004
[3] Y.Fan, N.Lafferty, A.Bourov, L.Zavyalova, B.W.Smith, “Air bubble-induced light-scattering effect on image quality in 193 nm immersion lithography”, J. of APPLIED OPTICS Vol. 44, No.19,2005
[4] M.S.Arulampalam, S.Maskell, N.Gordon, T.Clapp, ”A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking," IEEE Transactions on Signal Processing, vol. 50, No. 2, 174-189, 2002